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The devil is in the details: The successes and limitations of bureaucratic reform in India

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ABSTRACT

Using a biometric technology to monitor the attendance of public health workers in India resulted in a 15 percent increase in staff presence, particularly for lower-level staff. The monitoring program led to a reduction in low-birth weight babies, highlighting the importance of improving provider presence. But, despite the government initiating this reform, there was ultimately a low demand by the government to use the higher quality attendance data available in real time to enforce their existing human resource policies (e.g. leave or salary deductions) due to logistical challenges and a not unrealistic fear of generating staff discord or increase in staff attrition, especially among doctors, who showed the least improvement in attendance. While we observed some gains from this type of monitoring program, technological solutions by themselves will not improve attendance of government staff without a willingness to use the data generated to enforce existing penalties.

1. Introduction

Our models to analyze bureaucratic behavior often derive from the principal-agent-citizen framework. The principal—the government—designs a program around a specific goal, and the agents—the various bureaucrats—implement it (for a discussion of the literature, see Banerjee et al. (2013)). The challenge lies in bureaucrats naturally having different incentives than the government in terms of how they would administer the program, combined with the government's inability to perfectly monitor the bureaucrats' behavior. It, thus, follows that technological improvements in monitoring to increase the probability of getting caught engaging in a wrong behavior—along with increasing penalties for doing so, either financial penalties or other forms of stigma that may affect one's career trajectory—could, in theory, better align the bureaucrat's incentives to the government's. However, just monitoring along one dimension of work may not necessarily improve the program outcomes if the bureaucrat needs to undertake a series of different tasks—and not just the monitored one—to improve outcomes. It may even exacerbate problems if the monitoring harms the bureaucrat's intrinsic motivation to undertake the complementary, unmonitored tasks (Holstrom and Milgrom, 1991; Benabou and Tirole, 2006).

We focus on a particular form of malfeasance: the absenteeism of public health care workers. Bureaucratic absenteeism is a common problem around the world and one that has defied many efforts to tackle (e.g. Chaudhury et al., 2006). Even in the fairly well-off Indian state that we study (Karnataka), staff are often missing: for example, doctors in the public-sector primary health centers (PHCs) were present only 36 percent of the time in our baseline survey, but rarely took a "formal" leave day. If health care workers are absent, citizens may go without essential primary care and, especially, women may choose not to seek antenatal visits or have a delivery by a trained physician. In the long run, this can dissuade citizens from even approaching public health care facilities for accessing care.[1]

Due to the high absentee rate, in 2010, the National Rural Health Mission (NRHM) of Karnataka—the lead department for the delivery of health services in the state—designed a program to enforce their attendance policy, which existed on the books for decades, but was rarely adhered to in practice. Specifically, they developed a system that utilized a biometric monitoring device to digitally capture the thumb print of each staff member at the start and end of the work-day. The data were then to be uploaded daily —via a cell phone—to a central office that was tasked with providing detailed attendance information to supervisors in the head office and field and to the PHCs, and ensuring that the staff's "leave days" were properly deducted on the days that they were absent.

This pilot program provided a unique opportunity to study

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[1] For instance, India launched a conditional cash transfer (CCT) program, *Janani Suraksha Yojana* (JSY), to promote institutional births.

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an organically-developed, government program that aimed to use the latest technology available to increase the monitoring of and incentives to both mid-level (doctors) and lower-level bureaucrats (e.g. nurses, laboratory technicians, etc) working in Primary Health Centers (PHCs) which as the name suggests are meant to be the primary providers of rural health care. The government piloted the system in about 140 PHCs in five diverse districts across the state, thus allowing us to randomize which 140 out of the 322 total PHCs in these districts received the intervention. We collected detailed data in order to understand how the system affected the bureaucrats' work behaviors and to test whether the system would ultimately affect citizen health. Note that even as a pilot, the introduction of this system was a sizable policy change: over 300 government employees and about two and a half million citizens (in the catchment areas of the treatment PHCs) had the potential to be impacted by the project.

Previous studies from the non-profit setting showed that these kinds of programs can be successful (Duflo et al., 2012). The non-profit setting provides a clean empirical test of the principal-agent model, as non-profit programs are usually conducted on a relatively small scale requiring few intermediate agents. In addition, in a non-profit setting it is relatively easy to alter the employee contracts to provide financial incentives.[2] However, a monitoring and incentive system may work very differently in government settings given the much larger scale that leads to decentralization of different tasks, the varying incentives of different government staff, and immense complexity of human resources processes including rigid civil service rules for incentives and discipline and multiple supervisory authorities. And yet, such monitoring and incentive systems are much more important in government settings precisely for these reasons and because governments in many developing countries like India continue to be the biggest providers of health care and education where absenteeism is highly prevalent. Consequently, more recent work has focused on introducing these kinds of systems into government (see, for example, Banerjee et al. (2008) and Callen et al. (2016)), but with varying levels of success.

Given our project set-up, we are thus able to contribute to this existing literature in three main ways.[3] First, we test an organically developed and comprehensive program at a very large scale, with a partner who fully intended to scale it up across the entire state if found to be effective. Banerjee et al. (2008), for example, had an incentive scheme introduced just for the experiment, and it was only enforced for sub-center nurses on one-day a week (since the nurses' primary duties were in the field). In our paper, we study a program developed by the government to use much more sophisticated technology to monitor their staff at primary health centers—who are required to be in the office on all days—and use the data to better enforce the existing government rules. Thus, with the detailed data that we have collected, we can not only test whether the monitoring has an effect on absenteeism, but we can better understand the challenges that arise when trying to implement these theoretical models within government settings and the reasons for its success or failure.

Second, we study the effect on different types of workers, from doctors to nurses to pharmacists, who may face different types of incentives and penalties within the government and may have differences in their outside opportunities. Importantly, across these very different workers, we also explore issues relating to their job satisfaction, retention, preferences to be in treated PHCs, and even corruption levels. Finally, while the previous research studied the effect of such systems on bureaucratic behavior, we additionally study the impact of the system on patient outcomes—health, payments and satisfaction.

Overall, health care workers increased their presence by 14.7 percent as a result of the introduction of the monitoring technology, despite some of the implementation challenges that we detail below. Disaggregating by time of day, we observe large increases in attendance in the morning, suggesting that the program effect may have been driven by reducing tardiness, which thus increased the total time spent in the PHC conditional on a staff member showing up at all. Importantly, there was substantial heterogeneity, however, within the PHCs: there were no observable treatment effects for doctors who are in charge of the PHCs, but instead the overall treatment effect appears driven by an 18 percent increase in the presence of the lower-level staff—the nurses, lab technicians and pharmacists. These results are consistent with the qualitative evidence that we collected suggesting that, for doctors, public sector jobs, especially those in rural areas, are increasingly becoming less attractive than private sector jobs as evidenced by a number of vacant doctor positions in PHCs. Therefore, the government—which is worried about doctor recruitment and retention—is more likely to let the rules slide for them, even when they have very good information on their absence. On the other hand, public sector jobs for nurses continue to be better in terms of pay, benefits and work-life balance than private sector ones and thus it is more feasible to impose more stringent regulations on them. Note that overall treatment effect was fairly constant for the first 10 months of follow-up, but then somewhat declined in the final months as the pilot program wound down.[4]

An increase in staff presence may not necessarily affect citizen health. The production function for health may require several concurrent tasks, and so just increasing attendance may not have a large enough effect. It may even exacerbate problems if the incentives harm the intrinsic motivation of the staff to participate in these other tasks. Moreover, only nurses and pharmacists were present more in the treatment PHCs—it is possible that any gains to health would come only from doctor attendance. Finally, at the extreme, it is possible that health care worker quality is so low (for example, see Das and Hammer (2005), Das et al. (2008) and Das and Hammer (2007)) that any increase in attendance would not have a noticeable effect on patient health. Thus, it is an empirical question as to whether we would observe gains to health from increased monitoring and staff presence. We find that health outcomes improved: there was a 4.6 percentage point decrease in the probability of being born below 2500 g. The level of antenatal visits was already high and did not alter as a result of the treatment, so the birth weight outcome was not due to an increase in visits. However, it is possible that the longer time spent by nurses and other staff at the PHC led to longer, more helpful visits; for

[2] For example, in Duflo et al. (2012) about 60 one-teacher schools were in the treatment. In fact, once the program was scaled up to the control group as well, the NGO had to decentralize the running of the program to different regional staff to administer rather than having one central office.

[3] This paper also builds upon the literature that explores the introduction of technological solutions to various aspects of government—with varying levels of success—including the introduction of electronic voting machines (Fujiwara, 2015), computerized land registration systems (Deininger and Goyal, 2012), electronic identification cards for the beneficiaries of social assistance programs (Muralidharan et al., 2014), and smart-phones to "monitor" officials who "monitor" lower-level bureaucrats (Callen et al., 2016). This paper contributes not only by exploring the impact of these programs, but also by exploring how the government's conflicting goals may impact whether technology will have sustained impacts.

[4] There were several possible reasons that the project began to wind down. First, the head of the NRHM who introduced the program changed and there was rapid turnover of successors for whom this was no longer a priority project. Second, the research team also became less involved in the day-to-day monitoring of the system.

example, there is evidence that the quality of antenatal care increased in the treatment PHCs along dimensions that were initially low (e.g. the disbursement of iron folic acid its).[5]

One of the biggest changes as a result of the intervention was a change in delivery methods: deliveries conducted by doctors increased by about 16 percent in the catchment area of the treatment PHCs. At first, this seems at odd, as doctor attendance did not increase as a result of the treatment. However, delivery location also changed, with more women in the treatment areas delivering in the large public and private hospitals. Some of this may have been due to better triage by the more present nurses and pharmacists, sending women with high-risk pregnancies to the more advanced hospitals. Moreover, the women who had just delivered in the catchment area of the treatment PHCs were less satisfied with staff attendance at the treatment PHCs, so it is also possible that the treatment simply increased the salience of the absenteeism when the women came in for their antenatal visits.

One worry in principal-agent models is that by increasing monitoring along one dimension, employees will seek to compensate themselves along other (unmonitored) dimensions given the costs they incur due to the additional monitoring. There is some evidence that this may have occurred, with an overall increase in delivery costs. Some of this may have been due to doctors diverting women to their private practices to earn additional fees, but delivery costs also increased for those who delivered at the PHC. Moreover, women get a number of government entitlements for delivering in an institution (both cash and in-kind payments). Women in the treatment areas were about 7 percent less likely to know about their state entitlements than those in the control areas (significant at the 1 percent level) and they were also less likely to actually receive their entitlements (p-value of 0.105). Thus, while the program was designed to reduce one particular form of corruption (fraudulent absenteeism), it may have exacerbated other forms (e.g. “extra” payments, lost entitlements) in response.

The principal-agent models often have very little to say about the principal, their incentives, and their ability to credibly implement additional monitoring and incentives. However, the principal is part of a larger system and, in real life, faces many additional challenges in implementation. For example, in this case, while the state government initiated and designed the pilot project with a stated goal of reducing absenteeism, they did not actually follow through in using the better data to actually deduct the employees' leave balances. Some of this was due to the fact that because of cumbersome civil service rules and multiple stakeholders (detailed below), it was not straightforward to do so and, despite good intentions, just how difficult it would be was not well understood by the government at the start.

Other challenges in implementation arose from the fact that people are still required to implement the technology and not all people within the broader government system have the same incentives to do so. For example, the actual implementation of human resources policy of the state government is implemented by the sub-district health officials, who are in charge of monitoring the doctors. When interviewed, they divulge low expectations of what is considered good attendance: for example, they expect doctors to be present about half of the required days of the month. When asked to rank the PHCs under their domain from best to worst, we find that actual attendance is uncorrelated with rank, suggesting that attendance is not a serious criterion in which they judge the PHCs. As such, they approved most exemption requests by doctors for absences even though the state government had tried to severely restrict supervisor exemptions.[6] Even when the state government tried to motivate the sub-district health officials to better enforce the rules through a series of video conferences with them, an event study analysis reveals that these attempts yielded no change in absence rates.

However, there were also more fundamental conflicts *within* the amorphous principal about what the right goals are and how to achieve them. For example, there were many debates about how strongly to actually impose the monitoring due to a fundamental tradeoff: balancing a staff that followed the rules (e.g. being present most days of the week) with trying to retain staff and keep them motivated. Given the growing private sector, coupled with the fact that many PHCs are in less-desired remote locations, state officials often claim that they have to give the staff —particularly doctors—more leeway along dimensions other than salary in order to keep them motivated and not lose staff.[7] While initially, both types of staff were given the same level of exemptions—days they could miss without penalty—the state government internal debates led to doctors being given more exemption days than nurses. This view is not entirely without merit: doctors and staff nurses in treatment PHCs report significantly less satisfaction with their positions than the control just due to being monitored more, even without having the financial penalties imposed. Moreover, the treatment PHCs attracted fewer applications to transfer to, from nurses, lab technicians and pharmacists—the very group that was most affected by the intervention—than the control PHCs, although it is worth noting that overall treatment effect on this group is small and, even with this effect, citizens experience health gains.[8]

In short, this paper illustrates that while reforms based on principal-agent models have somewhat clear effects in theory, in practice they are difficult to implement in real government settings due to the complexity of the environment.[9] It also shows the limits of the use of technology to improve the delivery of public services if it is not combined with changes in the broader rules and regulations governing bureaucrats. Given the challenges of governments to credibly monitor—and penalize—their staff, this raises many questions about the best way to improve public sector performance. Given outside options of doctors, would improving work-life balance for doctors (i.e. requiring fewer days, but ensuring that they attend those days) be more effective in ensuring overall performance?[10] Moreover, since we find that monitoring has an effect on staff with lower outside options (and improves public health outcomes), can expanding public-sector nurses, rather than focusing on doctors, in rural areas be a more efficient way to improve the health? Or should the focus move to broader reforms where citizens are given information to better monitor local bureaucrats themselves in real time, which is now made

[5] However, we caveat that this is simply suggestive since we were not able to collect data on the length of the visits, but only on a few key indicators of what *actually happened* in the visits.

[6] Banerjee et al. (2008) also found that the primary health center officials continually granted exemptions to the sub-centers, leading the program effect to reduce after the first six months. Interestingly, in this case, the exemptions were entered into the system by the sub-district officials and thus easily monitored by the state level officials; even then, they had little hesitation granting exemptions.

[7] There may even be concerns about the type of staff who are recruited and stay. For example, Ashraf et al. (2015) show that higher ability staff are recruited when career benefits are posted rather than social benefits.

[8] We cannot say for sure that we would observe doctors choosing to leave the PHCs or choosing other PHCs had the monitoring been more greatly enforced on them because we realized an equilibrium where the doctors were not penalized or stigmatized enough to attend more and the overall fees paid out to doctors by citizens increased.

[9] This also contributes to a growing literature that compares how similar program fare across NGO and government settings, such as Bold et al. (2013).

[10] For an example of this, see Banerjee et al. (2012), which explores changes in human resource practices within the police sector in India.

possible due to technology,[11] or to give them choice between public and private health systems?[12]

The paper proceeds as follows: Section 2 describes the experimental design and data, while we present the results on staff presence and patient outcomes in Section 3. Section 4 describes the reform challenges. Section 5 concludes.

2. Experimental design, data collection, and sample statistics

2.1. Setting and sample

India has an extensive network of about 24,000 government-run Primary Health Centers (PHCs) that provide basic primary care to the poor, particularly those located in rural areas. These centers exhibit the common problems observed in many government bureaucracies across the developing world including staff vacancies, fraudulent absenteeism, limited budgets, shortage of medical supplies and poor infrastructure.

PHC Staff are required to sign-in every morning, with their attendance recorded on paper registers that are maintained at the PHC and very easy to manipulate.[13] As we further discuss below, there is significant absenteeism, with employees either missing full days or attending for only limited hours. Sub-district health officials, as well as local elected bodies (GPs), conduct surprise checks on the health centers. Qualitatively, these checks are not very frequent, and collusion between staff means that inspecting officials are informed either that the truant health staff is out doing field work or is sick.

When questioned about their absenteeism, the health staff often mention requirements for being in the field or in meetings, the long distance of many PHCs from the district headquarters where most of the doctors live due to the absence of “good living arrangements” near the rural PHCs, the absence of reliable and frequent public transportation, the lack of demand among the local population for their work, and the lack of appreciation among government and citizens of their service.[14] However, conversations with the state government and local citizens suggest that the primary reasons for high absence are the more lucrative private practices that many doctors run on the side and the lack of effective monitoring of health staff.

To address the absence problem, the National Rural Health Mission (NRHM), a government department in Karnataka (an Indian state with a population of 53 million), designed and raised funds to introduce an innovative biometric device to enforce the government's actual attendance rules, which were rarely followed in practice. They aimed to pilot the program called the “Integrated Medical Information and Disease Surveillance System” (“IMIDSS”), in all 140 PHCs of two districts to learn how the program would function. After conversations with the co-PIs, the intervention was instead spread to about half the PHCs in five districts—Mysore, Chitradurga, Dharwad, Dakshina Kannada, and Bidar—that were chosen to represent the diversity in income levels and institutional capacity across the state. Thus, our overall sample consisted of the 322 PHCs in these five districts.[15]

Note that with an expected catchment area of about 18,000 individuals per PHC, even this small pilot had the potential to affect health services delivery for the over 2.5 million individuals that belonged to the catchment area of the treated PHCs.

2.2. Experimental design

Out of the 322 PHCs, 140 were randomly assigned to be part of the pilot project, while the remaining 182 PHCs maintained the status quo. Details of each treatment are as follows:

2.2.1. Comparison PHCs (status quo)

The PHCs are open daily from 9a.m. to 4:30 on weekdays (including Saturdays), and 9a.m. to 1:00p.m. on Sundays and holidays. The staff are required to work seven days a week, but nurses, laboratory technicians, and pharmacists are allowed to take the second Saturday of each month off. A fraction of the PHCs are open 24 h a day (about 40 percent in our sample), with most staff present for the day shift only and a different set of nursing staff present at night. During work hours, the PHC employees are expected to be physically present at the PHCs, except for monthly meetings and the occasional field visit if approved by a supervisor (the sub-district health officer for the doctor, and the doctor for all other staff).

There is an official leave policy, but it is not followed in practice. In addition to national and state holidays, each staff member has 15 days of guaranteed “casual leave days” a year, which they need to use or lose within the calendar year; doctors are responsible for approving and maintaining the records for these leave days (including for themselves). In addition, each staff member can accumulate up to 30 days of “earned leave days” each year. Deductions of earned leave are maintained at the state-level, Accountant General office. These days are valuable because unused days can be carried forward to the next year and cashed out in small amounts every year or completely at the time of retirement. Thus, the staff do not like to officially “use” these days to take leave and prefer instead to cash them out.

The sub-district health officers (Taluk Health Officers, or THOs) are responsible for implementing the health programs of Department of Health and Family Welfare within each sub-district through the network of PHCs and a network of sub-centers that fall under the PHCs. They are also in charge of training, as well as the day-to-day monitoring of the PHC staff. However, they do not have the direct authority to enact disciplinary action: the power to take action against lower-level civil servants (e.g. Nurses, Lab Technicians, Clerks) rests with the District Health Officer (DHO), while the authority to take action against higher-level civil servants (e.g. government doctors) rests only with the health department headquartered in Bengaluru, the state capital. The sub-district officer can only submit complaints regarding the staff members or PHCs to the district health office, who then also involves the state government if the issues involve a doctor.

[11] See Alatas et al. (2013) and Björkman and Svensson (2009) for examples decentralizing the monitoring of local officials to citizens.

[12] Andrabi et al. (2016) showed large effects of increased competition between public and private schools, while Banerjee et al. (2015) showed that an increase in competition in food distribution systems was unsuccessful due to elite capture.

[13] For instance when staff return to work after a few days of absence, they just add in their signature for all previous days of absence and unless a supervisor checked the records on the days the staff were absent, there is no way of detecting such “late” sign-ins. And even there, it is very hard for the supervisors to verify if told that the staff is “out in the field” or “gone to district headquarters to collect supplies.”

[14] One reason often cited for this lack of demand by the government was that most people prefer to either go to sub-district or district hospitals that have better facilities and specialist doctors, or to private health care (including traditional practitioners). However, in interviews with citizens, they often mentioned that they would prefer to visit the local PHC, but cited the absence of doctors (or even closed PHCs), “unsatisfactory” treatment, and the lack of medicines as the reasons for not using them.

[15] The initial government list consisted of 350 PHCs. However, upon investigation, 20 were not actually PHCs (but rather Community Health Centers or Maternity Centers), 1 was a duplicate PHC, and 1 was adopted by a medical college and not fully under the government control; these were excluded from our sampling frame. Six PHCs refused to participate in any surveys and pilot projects, leading to the final sample of 322.

Fig. 1. Medical Information and Disease Surveillance System.

2.2.2. Treatment PHCs

The government aimed to utilize the biometric devices to enforce the existing leave rules for the PHC staff through improved attendance monitoring. The state government supplied each PHC with an "IMIDSS device," consisting of a fingerprint reader (FPR) and a multipurpose mobile phone device (Fig. 1). Each staff member was required to scan their thumb on the FPR when they arrive and when they leave the PHC. The FPR captures a date/time stamp for the thumb prints which have been initially registered in the device. At the end of each day, a designated staff member at each PHC is responsible for connecting the mobile phone to the FPR to transmit the fingerprint data to a dedicated server located in the NRHM office in Bengaluru, from where the pilot project was managed. The PHC was also required to enter in the mobile phone details on disease counts and information on women who gave birth at the PHC.[16]

There are several important contextual details: First, while the PHC employees were supposed to primarily be present at the PHC, they were allowed some flexibility for attending meetings or for occasional field visits for special campaigns like school health visits or pulse polio days. Specifically, in increments of half-days, the doctor was allowed a maximum of 5 full day exemptions for work outside the PHC each month, the staff nurse was allowed a maximum of 2 full-days, and all remaining staff was allowed a maximum of 3 full days. The doctor could approve all of these allowed exemptions (including for himself), but any exemptions above and beyond this were to be approved by the sub-district health officers, who were informed by the state government repeatedly that approval for these additional exemptions should be rare and that their patterns of granting exemption would be reviewed in turn by their supervisor, the district health officer, who in turn was monitored by the nodal officer for the program based at NRHM office in Bengaluru. In practice, the sub-district officer approved almost all of the exemptions that were submitted. Rarely, they refused, but this was only for lower level staff and for obvious cases of misconduct (such as absences that lasted several weeks at a time).

Second, even with the precise attendance data, it is not straightforward to use this data to actually deduct leave. Using the dates and times of the fingerprint readings, the state government can calculate the number of working days of each staff member in a given month. At this point, the government also can collect the exemption records from the sub-district offices and the leave days taken from the machines to calculate whether there is a shortfall in attendance, and if so, by how many days. At this stage the state-of-the-art technology, real time data and this automated computation of attendance has to confront state civil service rules that in many cases were drafted many decades ago and have only changed in minor form rather than substance or process over the years. The shortfall is supposed to be communicated in the form of a memo (a "show cause notice") to each PHC staff, which allows them to offer explanations as to their unauthorized absence. Once the memo is returned, it is acted on by the sub-district health officer, who is authorized to debit the days exceeded from the staff member's leave balance. First, they deducted the casual leave days that are accrued to the staff and expire annually; to do so, the sub-district officer needs to communicate the deductions to the doctor, who maintains these records at the PHC. After the casual leave days are depleted, the sub-district officer can start to deduct the earned leave balance; this requires that the sub-district officer again give a written notice to the relevant staff member making them aware of the intent to deduct their earned leave and giving him/her an opportunity to respond. After receiving the reply (which itself can delay the process inordinately), the sub-district officer determines whether to accept the explanation (in which case an exemption is granted) or reject the explanation and send a request to another official outside NRHM—the Director of Health and Family Welfare in Bengaluru—with detailed reasons for recommending a leave debit. If the leave deductions are approved by the Director, the request is then forwarded to the Accountant General office, a different department within the government. Given how effort and time intensive this process is, it is not surprising that most supervisors themselves hesitate to take disciplinary action, except in the most egregious cases. As we discuss below, only in very rare cases did the truant staff receive a formal "show-cause notice" from the state government and the sub-district officers never made any real efforts to actually deduct the unauthorized absences from the leave balances. Because these HR rules uniformly apply to all civil servants in the state government, not just in PHCs or even the health department, they are close to impossible to change without a huge political and bureaucratic will and effort.

Third, to motivate staff, the state government announced staff-level and PHC-level awards (prizes) that were linked to the attendance data for the PHCs in the treatment group. Since there were concerns around awarding cash prizes to PHCs or staff, the government instead proposed non-monetary awards such as certificates or honor rolls recognizing "Best PHC for overall attendance" and "PHC staff with highest attendance." However, during the Annual Doctors' Day in 2012, none of the awards that were given out were actually linked to the IMIDSS system data.

Fourth, to prevent damage or the misuse of the device, the government appointed one staff member at each PHC—typically either the pharmacist or the lab technician—to be in charge of the device.[17] The government provided this person with Rs. 500 ($9.10) per month to ensure that the device was functioning.

[16] Senior officials were concerned that if the system "looked" too focused on attendance, there would be resistance. Thus, it was decided that additional health data would be collected to frame the program as a general program to improve the PHC functioning. In practice, the disease counts were never used by the government in planning. Moreover, most of the staff recognized that the machines were primarily focused on attendance: for example, one staff nurse from a treatment PHC referred to it "Punch-in and Punch-out machine." At all levels of administration, the system was commonly known as "the Biometric Program," showing the ultimate belief that the system was in place to address attendance, rather than collect disease counts.

[17] In addition, the government also appointed a Block Program Manager (BPM) from each sub-district to respond to questions on how to use the system, as well as to arrange for repairs and the replacement of broken machines. They were provided up to Rs. 1000 ($18.18) per month for this work: each time a device was inoperable due to mishandling, Rs. 100 ($1.82) per PHC per day would be deducted from the total and they would be fined Rs. 25 ($0.45) per PHC for each day that data was not uploaded for reasons other than network or server failure. Again, the disbursement of these payments had similar budgeting and delivery issues as that of PHC level staff.

However, this payment was performance-driven: for each day in a month that the device was not functioning (and hence not uploading data), Rs. 50 ($0.91) would be deducted for that month; thus, if a device was not functioning for ten or more days in a month, he or she would not receive any payment for caring for the device. However, any disbursement of cash required approval of the annual Program Budget by the National Health Mission Directorate of the Government of India by March for the upcoming financial year and this posed a challenge. In the first fiscal year of the program, every appointed staff member received a bulk payment for the full amount, irrespective of machine functioning; this was done to motivate these staff members and as a promissory gesture. In the second fiscal year, the disbursement of payments did not consistently happen on a monthly basis.

Finally, during the course of the pilot study, it would be near impossible to keep knowledge of the experiment from the control group and vice versa. Thus, from the start, all staff members were informed of the pilot project and informed that selection into the pilot was at random. Given the initial plans to scale the program after one year, the government informed all staff members that they were testing the system this year to work out the bugs in it, and that it would be expanded to all PHCs the following year.

2.3. Randomization design and timing

The unit of randomization was a Primary Health Center (PHC). Given that the government had a budget to procure a maximum of 150 machines (including 10 spares), we randomly selected 140 PHCs from the 322 PHCs in the chosen districts, stratified by the 29 sub-districts ("taluks"). In four districts—Chitradurga, Dharwad, Dakshina Kannada, and Bidar—we selected about half the PHCs in the district. In Mysore, the biggest and most developed district, we selected 36 out of 120 (about 30 percent).

We had requested that staff transfers at PHCs be frozen to prevent potential movement from the treatment group into the control during the duration of the experiment, and this was agreed upon by the government. However, people do join and leave the service. The transfer decisions and placements for new hires for the entire department are typically decided upon each June through a systematic program called "counseling" that is held in Bengaluru. However, while the government made efforts to not take the program into account during the counseling, individuals do express location preferences during the counseling meetings, and the additional monitoring at the treatment centers was well-known. Thus, we assigned the few staff that transferred within our sample their original treatment, dropped all new staff members from the attendance analysis, and then systematically explored the entry and exit in the treatment PHCs.

As shown in Fig. 2, in July 2010, we conducted random checks to assess the rates of staff presence in the baseline and conducted a baseline facility survey. These surveys were conducted in anticipation of the government's plan to deploy the IMIDSS system in September 2010. In practice, the machines were only procured in March 2011, and so we conducted a second baseline survey in the summer of 2011. After piloting at a few PHCs to ensure the functioning of the system, the government conducted training sessions and rolled out the system in Mysore district in July 2011. The training for the other districts (as well as a retraining for Mysore) was conducted in September to October 2011.

After the intervention commenced, we conducted seven rounds of random checks. We conducted the first round (August 2011) only in Mysore District, which received the system first. We conducted the subsequent follow-up random checks between September 2011 and November 2012. In November and December 2012, we also conducted a series of endline surveys with the various project stakeholders (facility survey, doctors, nurses, sub-district health officials, local elected officials, and women who had given birth within the timeframe of the experiment) to assess the impacts of the program.

2.4. Data collection

We administered several types of surveys. First, we conducted "random" checks on the PHC to assess the staff presence in the PHC. We conducted two rounds of unannounced checks to assess baseline attendance and seven follow-up rounds to assess program impact. For logistical purposes, we generally surveyed the PHCs within the same sub-district over concurrent days. We randomly assigned the time of day that PHCs were checked so that no PHC was always checked at the same time of day.

For each random check, the enumerator conducted a surprise visit at the PHC and recorded whether each staff member was present at the moment that he or she arrived; if it was closed on arrival, everyone was considered absent. The enumerator then inquired about who was transferred or resigned (they were subsequently dropped from the sample). Next, the enumerator counted the number of patients present at the time of the visit and the number of patients in hospital beds. For treatment villages, the enumerator additionally checked whether the IMIDSS system was in working condition and being used. Although the checks were infrequent, there was a concern that the monitoring associated with the random checks could affect attendance as well; therefore, 50 percent of the sample was randomly selected to be visited only in every other follow-up survey round so that we could test for possible Hawthorne effects.

Second, we administered a facility survey at the start (July 2011) and end (November to December 2012) of the study. This survey was designed to gather general information about the PHCs: hours of operation, number of staff, the number of patients, disease counts, quality of infrastructure, and available medicines and vaccines.

While conducting the facility survey during endline, we also conducted surveys with the doctor and one staff nurse at each health center to learn more about their background, work experience, perception of working conditions, and the system.[18] In addition, we also conducted interviews with the sub-district health officers, who are responsible for monitoring all PHCs (including staff attendance) in their sub-district to learn more about their interactions with the health centers.

Next, we interviewed members from the local government body (Gram Panchayats, or GP) that fell within the catchment area of the PHC to learn about the village demographics, their interactions with and perceptions of the PHCs, their perceptions of the GP quality, and their beliefs on the IMIDSS system. Due to monetary constraints, we interviewed GPs in all districts except Mysore. We interviewed the president of the GP in 61 percent of the cases and we interviewed the vice president in 11 percent of the cases; in the remaining villages, we interviewed an active member.

Finally, we conducted a survey of women who had given birth in the last year within the catchment area of the PHC. We randomly selected a village from the catchment area of each PHC for all districts other than Mysore and conducted a census of all women in that village who were pregnant during the experiment

[18] Not all PHCs that we attempted to interview were included in this survey. First, not all PHCs had a doctor or staff nurse employed as vacancies are common. Second, there were a small percentage of doctors and nurses who were never present during any of our attempts to interview them. In Appendix Table 1, we regress an indicator variable for whether the PHC was not interviewed on the treatment variable and sub-district fixed effects; PHCs were more likely to be missing in our sample if they were in the treatment, but this is not significant. The endline surveys are primarily used to understand staff satisfaction and management of PHC. If staff left the treatment PHCs at a higher rate due to being unsatisfied with the NRHM program, then we would underestimate the level of dissatisfaction. Thus, our estimates will provide a lower bound on the dissatisfaction levels with the program.

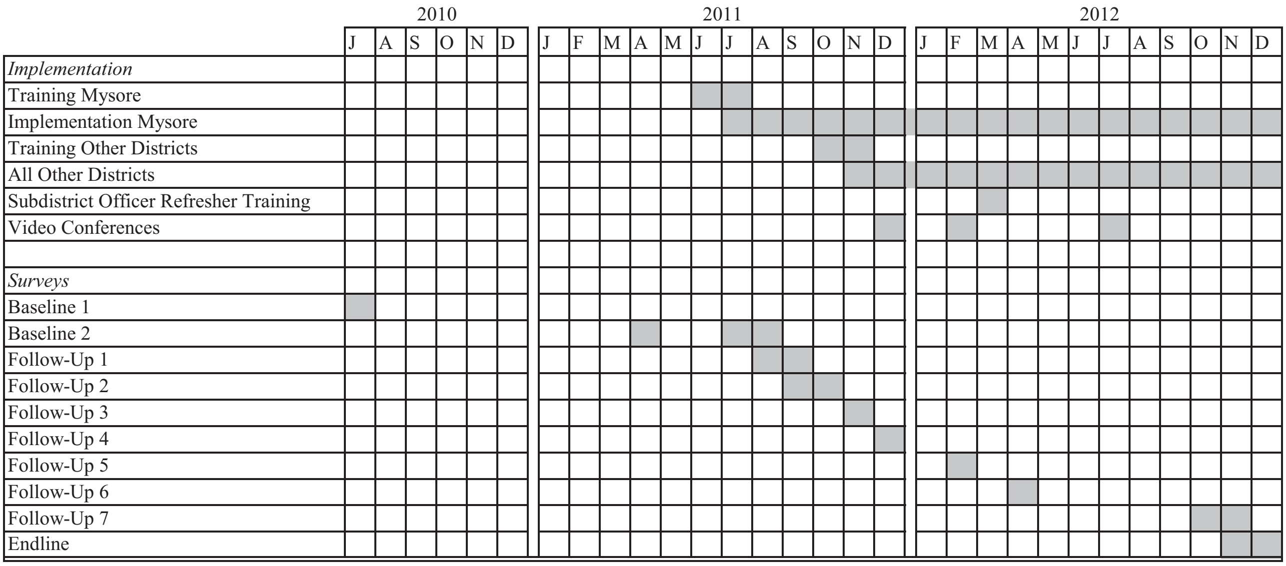

Fig. 2. Project timeline. Note: The endline phase of the project included surveys of facilities and interviews with project stakeholders, including: doctors, nurses, sub-district health officials, local elected officials (gram panchayat) as well as women who had given birth within the timeframe of the experiment.

and their pregnancy outcomes. We then randomly selected 4 women per catchment area who had given birth during the course of the experiment to learn about where they had given birth, who conducted the delivery, how much they paid, whether they had antenatal care, and their perceptions of the PHC.[19] During this visit, we also asked all the mothers for their baby's birth weight.[20]

In addition to the survey data, we obtained administrative data from the government on the program functioning. In particular, we obtained all data from the IMIDSS system, including both the biometric records and the disease counts collected within the system.

Finally, to better understand how the program was operating in practice, we and our team conducted extensive interviews with the government (state officials, district and sub-district health officers), PHCs staff and local residents during the course of the study, as well as recorded their field observations.

2.5. Summary statistics

Table 1 provides baseline sample statistics from the facility survey and the first two rounds of random checks. As shown in Panel A, the PHCs served, on average, around 13 villages, and claimed an average of 67 patients per day (or about 24,500 patients per year). About 40 percent of them were open 24 hours a day, while the remaining PHCs were on a 9am to 4:30 pm schedule.[21] Recruiting staff to rural or remote areas is a challenge for the state government, especially in the presence of a growing private health sector. This is reflected in relatively high rates of vacancies: for example, in the baseline, 20 percent of PHCs had at least one unfilled position for a doctor, 15 percent for a staff nurse, 37 percent for a pharmacist and 13 percent for a laboratory technician.

Staff presence is generally low: in the first round of the random checks, the nurses, lab technicians and pharmacists (henceforth, NLP for conciseness) were present in only 49 percent of the checks, while the doctors were there in 40 percent of them. These rates continued to remain low ten months later during the second round of checks: for example, the doctors were only present at the PHC in 32 percent of the random checks. While these numbers seem low, they are consistent with other studies: Banerjee et al. (2004) reported a 54 percent attendance rate of the PHC (and the larger Community Health Centers) staff in Rajasthan, while Chaudhury et al. (2006) found a 60 percent attendance rate in a nationally representative survey of PHCs in India, with doctors more likely to be absent than lower-level staff.

These rates are unlikely to be fully explained by field activities or other work activities (e.g. trainings, meetings).[22] The staff are primarily obligated to be at the PHC during operating hours, and those who have more limited field responsibilities (e.g. laboratory technician, pharmacist) exhibit the same low rates of presence as everyone else. Furthermore, Banerjee et al. (2004) tracked sub-center nurses in Rajasthan who were absent during their random checks, and found that the nurses were only in the villages attached to their sub-centers in 12 percent of the cases.[23]

2.6. Experimental validity

The first threat to experimental validity is that, by chance, the randomization leads to imbalanced groups. Appendix A Table 3 provides a check on the randomization; Panel A explores balance

[19] We did not want to interview women who had just experienced a miscarriage, a still-birth, or sudden infant death, as it was a sensitive time for them. Thus, we only conducted in-depth interviews with women who gave birth to a living child. If the intervention reduced infant mortality, the effect of the intervention on infant mortality could be biased downwards. Thus, this would provide a lower bound estimate of the effect of the program on birth weight. Nonetheless, in Appendix Table 2, we test for the effect of the program on stillbirths, miscarriages, or infant death at the time of birth. These are low probability events, and we do not observe any difference based on treatment status.

[20] In particular, we collected mother-reported, birth weight data. We ask households to see a health card when available, but not all households would necessarily have received one or still have it. This type of data collection is common in many developing countries, where birth outcome data are not systematically collected or available. For example, the main source of birth weight data in many developing countries is the DHS, which collects data in the same manner that we do.

[21] 9a.m. to 1p.m. on sundays and holidays.

[22] Even if we assumed that every month the doctors spent 5 days in the field and took 2 legitimate leave days (which are both unlikely), their attendance rate should still be 77 percent. Thus, there is a large scope for improvement.

[23] Hanna and Wang (2014) also played a series of laboratory games with these staff nurses which and showed that absence was correlated with cheating in the laboratory games. This further suggests malfeasance.

Table 1
Descriptive baseline statistics.

	Mean (1)	Std (2)	N (3)
Panel A. Facility Survey, July 2010			
PHC Open 24 × 7	0.39	0.49	323
Number of villages served	13.23	10.21	310
Number of patients seen daily	66.55	40.21	321
Doctor vacant	0.20	0.40	322
Staff nurse vacant	0.15	0.36	320
Pharmacist vacant	0.37	0.48	321
Lab technician vacant	0.13	0.34	321
Panel B: Presence, July 2010			
All staff	0.46	0.50	2027
Medical staff	0.46	0.50	1154
Doctor	0.40	0.49	336
Nurse, lab technician, pharmacist	0.49	0.50	818
Panel C: Presence, May 2011			
All staff	0.40	0.49	2139
Medical staff	0.41	0.49	1221
Doctor	0.32	0.47	359
Nurse, lab technician, pharmacist	0.45	0.50	862

Note: This table provides sample statistics from the baseline survey. The data presented in Panel A come from a facility survey that we conducted in 2010, while the data presented in Panels B and C come from the surprise random checks on the primary health centers. A post is vacant if there is at least one sanctioned position that is vacant at the time of survey.

across the PHC characteristics in the baseline facility survey, while Panel B tests for balance across the baseline presence from the random checks. The treatment and control groups appear fairly balanced along these dimensions: a joint-test across the facility measures yields a p-value of 0.81 and a joint test across the attendance measures yields a p-value of 0.26.

A second threat to experimental validity could stem from two potential forms of "monitoring" effects. First, even though we conducted the random checks relatively infrequently, there could be a concern that the checks affected staff presence as well. However, because the checks were conducted equally among the treatment and the control groups, it is unlikely that this caused a differential effect. Nonetheless, we randomly selected 50 percent of the PHCs to be visited at a lower frequency. Appendix A Table 4 shows that the monitoring frequency does not significantly impact staff presence.

Second, it is possible that others within the government system (e.g. local government bodies or sub-district officials) change their own monitoring of the PHCs as a result of the system. The direction of the effect is ambiguous. They may see the machines as a substitute for their own activities and monitor the PHCs less, or the system may make the absenteeism issue more salient and thus increase their own monitoring. This is not necessarily a threat to validity: the fact that they change their behavior based on the machines may occur in the actual scale-up as well, and thus may be an important policy outcome to consider. However, the worry is that their behavior changes are just due to the experiment: for example, suppose they have a fixed amount of time for monitoring activities, view the machine as a substitute for their activities and thus differentially shift all of their monitoring into the control group, whereas if the treatment was applied everywhere, there would not be a differential shift. In this case, we may underestimate the effect of the machines.

In Appendix A Table 5, we test for whether the treatment induced differential monitoring by either the sub-district health officer or the local government body (GPs). We find no observable relationship between the sub-district officials monitoring of the PHC and the treatment status (Columns 1 and 2). Contact between the local government bodies and the PHCs is already high, with 81 percent of the GPs having conducted at least one inspection of a GP in the last three months (Column 5). We find no significant differences in contact between the GPs and the PHCs, and in fact, the signs of the coefficients show no clear pattern in terms of direction (Columns 3–6).

Table 2
Was the system received and used?

	Data source (1)	Mean (2)	N (3)
PHC received device and mobile phone	Random check	0.99	572
Device and mobile phone both currently functioning	Random check	0.66	598
Data successfully transferred the day before the random check	Random check	0.67	566
Data was sent on the day prior to the random check	Administrative data	0.82	572

Note: This table provides information on the receipt and use of the IMIDSS system from both the random checks and the administrative data.

3. Results on system use, staff presence and health

3.1. Did the primary health centers use the IMIDSS system?

In Table 2, we document whether the treatment PHCs received the system and whether it was functional at the time of the random check. As no PHCs in the control group received the IMIDSS system, we simply present sample statistics for the treatment group. While all PHCs received the system, it was only currently functioning in 66 percent of the random checks. This malfunctioning was often due to a missing or uncharged phone: in 13.9 percent of the cases, the fingerprint reader was not in working order, whereas the phone was not working in 28.6 percent of cases.[24]

If the machines were functioning, the PHCs typically used them. In the random check data, 67 percent of the PHCs report uploading data to the state government the day before the check; this is consistent with the percentage of machines in working order. The rate of reporting data is even higher if we examine the administrative data from those same days: on 82 percent of the days, at least some data are recorded. The machine stores 40GB of data at a time, and so even if data is not uploaded to Bengaluru on a particular day, this implies that at least some staff used the fingerprint reader on those days and the data were eventually uploaded.[25]

As we discuss above, it was challenging to actually deduct leaves and demand to do so was low even by the supervisory staff at the state headquarters due to a combination of cumbersome processes and concerns about staff retention in the face of large vacancies of doctors. Thus, even though the PHCs tended to upload the data, the government did not end up using the data to enforce the existing attendance rules. Thus, while the intervention increased staff monitoring, it did not change the probability of penalty if one was shirking.

[24] Mobile coverage is fairly decent. In 93 percent of the random checks, the enumerator was able to detect a signal. In cases where there was no signal, it was due to fluctuations in signal, rather than persistence in non-coverage.

[25] Comparing the attendance data from the machines with the random checks, we do observe a correlation between the two. However, not everyone used the machine, even if they were present: in 43 percent of the random checks where the staff member was present, they did not record a single fingerprint that day. Conversely, in about 7 percent of random checks where we did not find the staff member present, the machine recorded the staff member as present for at least 5.5 h, implying that they completed their "day" outside of the official working hours of the PHC.

Table 3
Reduced form effect on presence (random checks).

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
Treat	0.0343**	0.0549***	0.0139	0.0725***	0.0112
	(0.0137)	(0.0165)	(0.0264)	(0.0194)	(0.0384)
Baseline	0.230***	0.144***	0.0315	0.168***	−0.0929
	(0.0173)	(0.0213)	(0.0358)	(0.0258)	(0.129)
Observations	8084	4659	1363	3296	1440
Control group mean	0.396	0.373	0.309	0.401	0.573

Note: This table provides the reduced form effect of belonging to a treatment PHC on attendance, by type of staff member. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. We include the baseline attendance measure as a control in these regressions. If the baseline is missing, we assign the average baseline attendance and include a dummy variable for when the baseline value was imputed. * $p < 0.1$.

*** $p < 0.01$.

** $p < 0.05$.

3.2. Did the intervention change health worker presence?

The natural question that follows is whether the additional monitoring had an effect on staff presence. In Table 3, we estimate the reduced form effect of the program on presence as measured by the random checks.[26] Specifically, we regress an indicator variable for whether the staff member was present during a given random check on a dummy variable indicating treatment status, one's average baseline presence rate in the random checks, and sub-district effects.[27] All standard errors are clustered by PHC. We only include staff who were employed at the time the intervention began, given the differential selection by new hires as discussed earlier; as Appendix A Table 7, Panel A, shows, the results are also robust to their inclusion.[28]

The introduction of the machines to monitor attendance led to a 3.4 percentage point—or 8.7 percent—increase in overall staff presence (Column 1 of Table 3). The medical staff experienced a 5.5 percentage point—or 14.7 percent—increase in presence (Column 2). However, there is heterogeneity in the treatment effect: there was no observable treatment effect for doctors (Column 3), but about a 7 percentage point—or 18 percent increase—for lower level medical staff, the NLP (Column 4).[29]

The difference between the doctors and the lower-level staff may stem from the relative differences in the stigma cost of being seen as "delinquent" by others within the system, even if salaries were not cut. For example, the 15 sub-district health officers that we surveyed also reinforced the notion that they did not perceive a day of absence by a doctor as negatively as a day of absence by a nurse: on average, the sub-district officials claimed that they only expected the doctors to be present 16 days a month (or about 54 percent of the time). In contrast, they expected nurses and other medical staff to be present much more often, between 23 and 24 days a month.

The difference may also arise from differences in outside options: the state-level staff often discuss that it is hard to monitor doctors due to high levels of vacancies and the relative difficulty of recruiting them against a growing private sector. To better understand the market for doctors and nurses, we interviewed students at several local medical colleges and nursing schools. Almost all of the nursing students stated a preference for government jobs to private sector ones on the grounds that the government jobs paid better, included better benefits, had more stability since you were less likely to be fired, and had more reasonable work hours.[30] For medical students, the picture was more mixed: a majority that we spoke to expressed a preference for the private sector—citing the higher salaries, better location, more potential for prompleotion, and less politics or fear of transfers. Medical students who preferred the government jobs cited that they preferred the benefits, little monitoring over their time, and stability (no chance of being fired). In fact, the idea that the government jobs were only competitive in recruitment due to flexible non-monetary benefits, and that the government jobs would be less attractive if those benefits disappeared, was repeated time and again by almost everyone that we spoke with.[31]

Finally, we tested whether the treatment increased overall hours of coverage by a doctor or a nurse: we regress an indicator variable for a doctor or nurse being present at the PHC on the treatment status and sub-district fixed effects (Column 5). We find no effect on overall coverage, which suggests that the nurses generally increased their presence during the hours when the doctor was also present and thus could also be aware of whether they were absent, providing further support to the idea that the stigma of being seen as delinquent by their superiors may drive the nurses' behavior.

3.3. Patterns in presence by location and time

We next explore potential patterns in the treatment effect. This is important because it allows us to provide insights if we want to generalize to other contexts (e.g. variations in institutional quality, etc.), as well as test what happens when there is less institutional support for the program. Note that in all of the following graphs and regressions, we continue to control for baseline presence and the sub-district fixed effects and to cluster the standard errors by the PHC.

In Fig. 3, we first explore the treatment effect by survey round. We cannot reject that the effect differs over time, although we qualitatively observe a shrinking of the treatment effect in the last

[26] We focus on the reduced form effect of the program, rather than the IV on attendance, because one can imagine the machines having an effect on staff behavior beyond increased attendance. For example, suppose that one did not increase one's attendance, but was now worried that citizen complaints can have a larger effect on their promotions and awards because the better absence data would be scrutinized if there was a complaint. In this case, the staff member could increase their performance while present, even if they did not increase their attendance.

[27] If the baseline is missing, we input it with the average and also include a dummy variable indicating imputed baseline values. In Appendix Table 6, we explore the robustness of the estimates to varying the control variables. The results are near identical when we omit the baseline control (Panel A). As expected, we lose some power when omitting the strata fixed effects, but the statistical conclusions that the NLP are more likely to be present does not change (Panel B). In Panel C, we include individual-level control variables for gender and years at the PHC; again, the results are near identical to those in Table 3.

[28] Note, that we also test the robustness of the results to dropping individuals who left the PHC from the sample in Panel B of Appendix Table 7; the results from the balanced panel are near identical to that those with their inclusion.

[29] We group together nurses, laboratory technicians and pharmacists as they tend to provide triage services. In Appendix Table 8, we further disaggregate by staff position. There is a significant effect of treatment on both nurses and the laboratory technicians/pharmacists, and we find no significant difference between them. Thus, we feel comfortable grouping them together for the main analysis.

[30] In fact, the nursing students said that they viewed private sector jobs as a way to get experience while one is trying to get a government job.

[31] For example, one pharmacist we spoke to explained that her salary was nearly double when she worked in the private sector, but that the government job offered "family-work balance." Without this balance, the government job is less attractive than her previous employment.

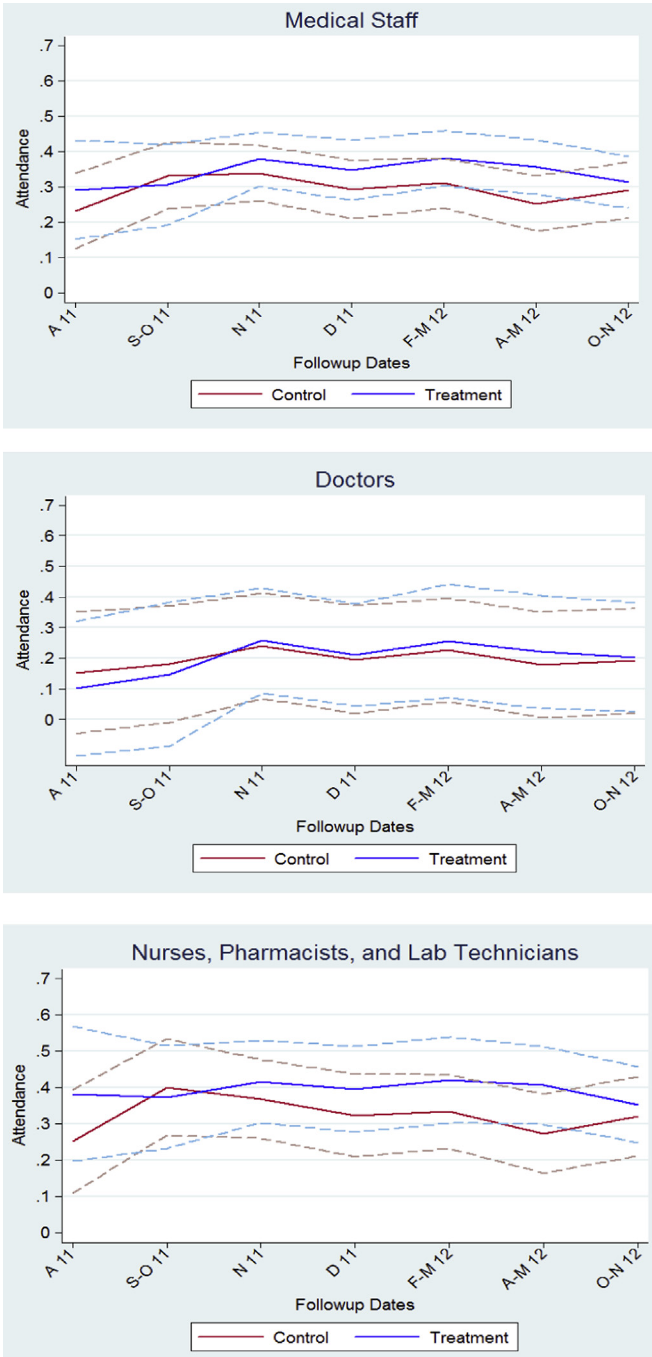

Fig. 3. Presence by follow-up round. Note: These figures plot attendance rates for the treatment and control groups by follow-up round, net of sub-district fixed effects.

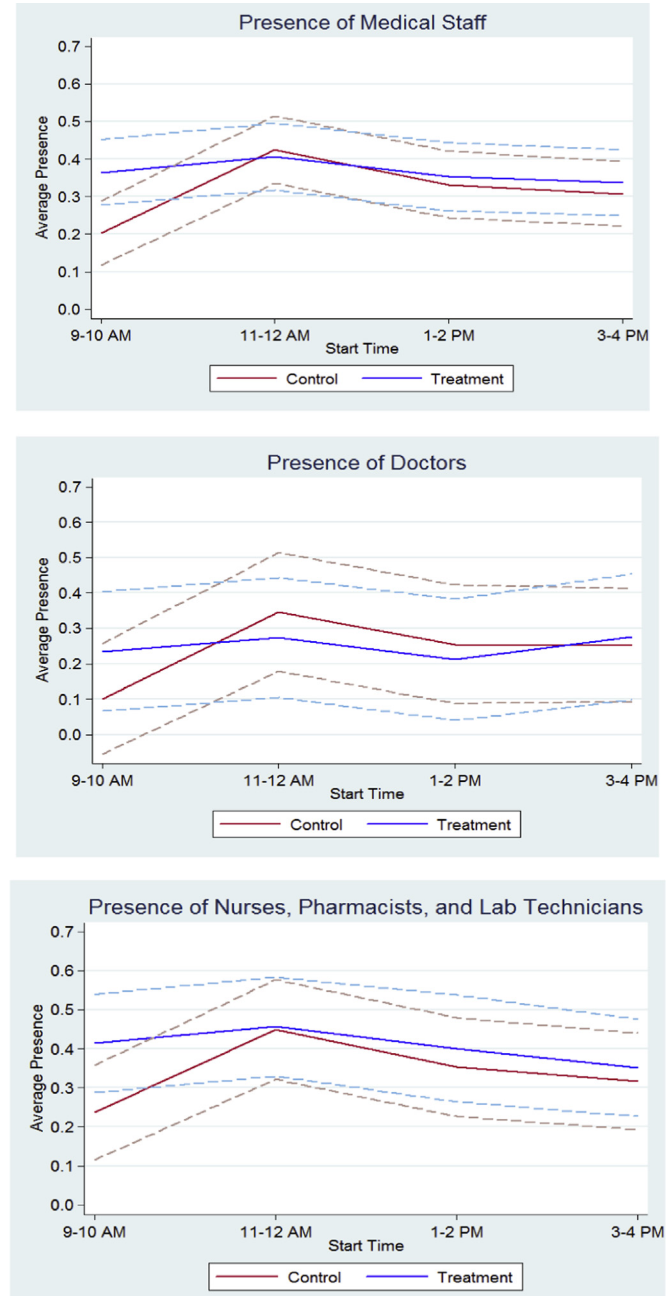

Fig. 4. Presence by time of day. Note: These figures plot attendance rates for the treatment and control groups by time of day, net of sub-district fixed effects.

round (October 2012), at a time where the leadership of the health department had been changing, the pilot began to wind down, and we had reducedr our support to the state government to implement the day-to-day running of the system.

Second, in Fig. 4, we randomly vary the time of day that the PHCs were chec minked. Interestingly, the biggest observed effect occurs in the morning (Appendix A Table 9 provides corresponding regressions). This is consistent with the interviews we conducted with the PHC staff: the nurses stated that the program forced them to take earlier buses and, in general, make a conscious effort to be at work on time. This also suggests that much of the effect we find might be driven by a reduction in tardiness, i.e. that the staff are more likely to come earlier and stay for the full day, conditional on coming at all. We also explore presence by day of the week in Appendix A Fig. 1. For medical professionals as a whole, it appears that the treatment effect occurs on most days, except Friday and Saturday (perceived weekend days).

Finally, in Appendix A Table 10, we estimate the treatment effect by district. The government purposely chose districts that capture Karnataka's socio-economic diversity, variation in institutional capacity and their a-priori belief about inter-district variation in absenteeism rates. The ordering of the table panels reflects this: Mysore is the most developed and closest to the capital while Bidar is the least developed and farthest. We find qualitatively similar treatment effects for Mysore, Dakshin Kannada, Chitradurga, and Dharward. In the least developed district, Bidar, we do observe qualitatively large effects for doctors (almost

Table 4
Reduced form effect on health care delivery (pregnancy survey).

	Self-Reported Birth Outcomes		*Antenatal Care*		
	Birth Weight (Grams)	Low Birth Weight	Number of ante-natal check-ups	Received at least 2 tetanus shots	Received at least 100 IFA tablets or 2 IFA bottles
	(1)	(2)	(3)	(4)	(5)
Treat	66.85*	−0.0462*	−0.00938	0.0295	0.106**
	(38.21)	(0.0272)	(0.235)	(0.0247)	(0.0410)
Observations	778	778	762	783	782
Control group mean	2828	0.177	6.271	0.863	0.392

Note: This table provides the reduced form effect of belonging to a treatment PHC on birth outcomes and antenatal care. All regressions are estimated by OLS, include sub-district fixed effects, and are clustered by primary health center. IFA stands for Iron Folic Acid Tablets. *** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

9 percentage points over a mean of *15 percent* in the control), but the coefficient is not significant at conventional levels (p-value of 0.28), perhaps due to smaller sample sizes.[32]

3.4. *Effects on health services delivery*

The intervention increased the presence of the nurses, laboratory technicians and pharmacists by 18 percent, but had no observable effects on doctors. The question that follows is whether this had any meaningful effects on health care provision and outcomes. On one hand, increased presence may allow for more time to treat patients and to triage high risk patients to the more advanced district hospitals. On the other hand, there are a number of reasons why there could be no effect: NLP could multi-task, i.e. show up more, but simply slack off when present. Perhaps only doctor presence affects health, or the increase in attendance was not large enough to have any noticeable effect on health? Or, even at the extreme, that health care worker quality is so low (for example, see Das and Hammer (2005), Das et al. (2008) and Das and Hammer (2007)) that any increase in staff presence would not have an effect on patient health.

To explore these issues, we surveyed 4 randomly selected women from a randomly selected village in each PHC catchment area who had recently given birth.[33] Tables 4, 5A and 5B provide these findings; note that we always include sub-district fixed effects and cluster by PHC.[34]

The intervention led to an increase in baby birth weight (Table 4). On average, babies weighed 67 more grams at the time of birth (Column 1 of Table 4) in treatment areas, and there was a 4.6 percentage point reduction—or a 26 percent decrease—in the probability of being born at or below 2500 g (Column 2).[35] This suggests that despite the fact that health delivery may be of low quality, an increase in quantity may have effects on health.

The number of antenatal visits did not change, but this was already quite high to start, with an average of 6.3 visits per woman in the control group.[36] Most women (86 percent of the control) received the two recommended tetanus shots already, and so while the treatment increased this by 3 percentage points, the change was not statistically significant at conventional levels. However, few women initially receive the recommended Iron Folic Acid (IFA) Tablets (39 percent of the control) and so this is a margin of ante-natal visit quality where there could potentially be room for gains. Indeed, this was the case, with the treatment leading to a 10.6 percentage point—or 27 percent—increase in receipt.[37] In short, this suggests that the mechanism through which the health effect may occur is not through increased antenatal visits, but may be due to changes in antenatal care along margins that were lower to start, perhaps through an increase in the time spent with patients or through the pharmacy being more likely to be open.

The composition of who conducts the delivery and where it is conducted also substantially changed (Table 5A): There was a statistically significant 8 percentage point—or 16 percent—increase in deliveries by doctors (Column 1), with deliveries by nurses and others falling (Columns 2 and 3). At first glance, this seems surprising, given that the intervention had no discernable impact on the doctors' overall attendance. However, the intervention led to a shift in where deliveries occurred: we find that the deliveries were 8 percentage points—or 28 percent—less likely to occur at the PHC (Column 6) and home deliveries—albeit low to start—were almost completely eliminated in the treatment group (Column 4). Instead, it appears that the women in the treatment areas moved to delivering at the larger public hospitals or the private hospitals (Column 7).[38]

There are several possible explanations for these compositional shifts in delivery patterns. While we cannot conclusively point out which is most responsible, we can provide some evidence on the likelihood that each contributed to the observed effects. First, if the staff were present more and spent more time with patients during the antenatal visits, they could have also better triaged high-risk pregnancies to larger hospitals. For example, we observe that women with late-term births are more likely to deliver in a private or large government hospital in the treatment group (a 12 percentage-point difference with p-value

[32] In Appendix Table 11, we test whether the treatment effect varies by whether the PHC is open 24 h a day or not. Staying open 24 h a day places more demand on the staff, even though there are more typically more staff employed. It is also much more difficult to monitor nurse attendance for these PHCs as there may be multiple shifts. We find that much of the effect of the NLP occurs in PHCs that operate only during the day. However, 78 percent of the PHCs in Bidar are also 24 h PHCs, which also has the lowest institutional capacity, and so it is hard to distinguish if this effect is driven by the hours of operation of the PHC or the locations.

[33] For cost considerations, we did not conduct the survey in Mysore district.

[34] We also collected data on the number of patients present at the PHC during the time of the random check. On one hand, we may expect this to increase if citizens learn about the program and utilize the PHC more. However, on the other hand, we might expect that more staff presence would lead to less waiting time and quicker discharges. Thus, the predictions are ambiguous. Nonetheless, we provide the findings in Appendix Table 12; we find no discernable effect on either the number of patients either waiting at the PHC to be seen or in beds.

[35] It is possible that if the baby was delivered at home, rather than an institution, the baby was less likely to be weighed. However, only 2 percent of deliveries were conducted at home and the results on birth weight are the same if we drop these women.

[36] While we do not know where all the visits occurred, we do know that over 70 percent of women received a tetanus shot at the PHC, which suggests that a large majority of visits occur at the PHC.

[37] Note that (1) The treatment effects we observe are larger than those reported in the literature for the effects of iron and folic acid supplementation on baby birth weight (for example, Siega-Riz et al. (2006) and Yasmin et al. (2001)). Likely, the increase in baby birth weight suggests that the increase staff presence may have also affect a series of different aspects of antenatal care (e.g. increased discussions on nutrition, etc.). However, we were only able to measure a subset of different interactions between staff and patients due to cost considerations. (2) Unlike previous studies that link an increase in iron supplements to terms of birth (see, for example, Zeng et al. (2008)), we do not observe any differences in term of birth.

[38] However, note that these effects, while positive, are not individually significant (Columns 8 and 9).

Table 5A
Reduced form effect on type of delivery (pregnancy survey).

	Who performed delivery?			*Delivery Location*					
	Doctor	Nurse	Other	Home	NGO or sub-center	PHC	Large public or private hospital	Large public hospital	Private hospital
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat	0.0801**	−0.0479	−0.0322*	−0.0259**	0.00347	−0.0792**	0.102***	0.0526	0.0490
	(0.0362)	(0.0367)	(0.0164)	(0.0114)	(0.0100)	(0.0351)	(0.0373)	(0.0401)	(0.0327)
Observations	783	783	783	775	775	775	775	775	775
Control group mean	0.501	0.437	0.0617	0.0350	0.0189	0.288	0.658	0.434	0.224

Note: This table provides the reduced form effect of belonging to a treatment PHC on type of delivery. All regressions are estimated by OLS, include sub-district fixed effects, and are clustered by primary health center.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 5B
Reduced form effect on satisfaction and costs (pregnancy survey).

	Standardized Satisfaction Index		*Entitlements*		
	Staff availability	Staff quality	Log (Cost)	Knowledge	Received
	(1)	(2)	(3)	(4)	(5)
Treat	−0.144*	−0.0421	0.789***	−0.188***	−0.131
	(0.0777)	(0.0882)	(0.215)	(0.0557)	(0.0802)
Observations	775	773	775	785	785
Control group mean	0.0894	0.0349	6.810	2.834	1.861

Note: This table provides the reduced form effect of belonging to a treatment PHC on patient satisfaction, delivery cost, and entitlements. All regressions are estimated by OLS, include sub-district fixed effects, and are clustered by PHC. The satisfaction variables range from 1 ("very dissatisfied") and 4 ("very satisfied"); we standardized these variables and averaged them by category. We construct the log cost variable by: taking the sum of all fees paid as reported on the endline survey; top-coding those values at the 99th percentile; adding 1 (to handle zeros); and taking the log of those values. The entitlements are the state programs that women are entitled to upon delivery, regardless of delivery location. ** $p < 0.05$.

*** $p < 0.01$.
* $p < 0.1$.

of 0.145).[39] On the other hand, while older women (who may be higher risk pregnancies) tend to deliver in these larger hospitals, we do not observe a difference in the treatment effect on delivery location by age.[40]

Second, it is also possible that the machines changed the citizen's perceptions of the treatment health centers. In particular, the additional monitoring may have increased the salience of the doctor's absence, leading the present staff members to relate the idea of the absent doctor to patients. When we asked the women to rate different aspects of the PHC, those in the treatment group were significantly more likely to be unhappy with the availability of the PHC staff (Column 1 of Table 5B), despite the fact that there was no perceived difference in PHC quality by treatment status (Column 2). This suggests that the treatment may have shined a light on public sector absence, leading women shift away from the PHCs.

A final potential explanation is more cynical: the monitoring system placed a real burden on the PHC staff, *even* if they did not fully change their behavior. In response to the additional costs placed on them by the monitoring, the staff may have chosen to compensate themselves in other ways. While they do not formally or readily admit it, many of the doctors have private practices or moonlight at private hospitals on the side. The fact that there may have been a shift to the private hospitals may signal that doctors are diverting patients there to increase their salaries. Moreover, many PHC staff members compensate themselves by charging patients who deliver in the government institutions extra.

It is challenging to measure this form of corruption since it is generally hidden. The increase in delivery costs (Column 3 of Table 5B) suggests that this might be occurring. In fact, the increase in costs in treatment areas is the same for those who deliver in the PHC and those who deliver elsewhere, thus suggesting that even those delivering in the PHCs are paying "extra" for deliveries (Appendix A Table 13).

In addition, the state runs a number of entitlement programs: low-income women can receive financial and in-kind transfers for delivery in any type of institution from the PHCs. Qualitatively, many women do not receive their full entitlements; instead, the PHC staff either keeps the entitlements or asks for a share. In Columns 4 and 5 of Table 5B, we explore the effect of the program on the provision of the entitlements: in treatment areas, the knowledge of entitlements significantly falls by almost 7 percent. Receipt of entitlements also falls by about 7 percent, but the p-value is 0.105. The patient is supposed to learn about these incentives to deliver in an institution during antenatal care and we do not observe a difference in the probability of getting a tetanus shot at the PHC, so presumably opportunities to gain knowledge of the incentives before birth should be the same. We also do not observe a difference in the treatment effect on knowledge of entitlements for those who deliver at the PHC and those who deliver elsewhere, suggesting that place of delivery does not determine knowledge. Thus, the results are consistent with the idea that the treatment staff do not provide women with their state entitlements at the PHC at the time of delivery, allowing the PHC staff to siphon off more of the entitlements and compensate themselves for the costs imposed by the additional monitoring.

In sum, children born in the catchment areas of treatment PHCs exhibited better birth outcomes than those in the control areas, potentially due to an increase in quality of antenatal care. However, the treatment shifted deliveries out of the network of smaller government hospitals and into larger hospitals (both government and private

[39] Note that there is no difference in the probability of late term birth across the treatment and control (p-value of 0.580).

[40] We also observe an increase in c-sections in the treatment group, but not significantly so (p-value of 0.179). It is also hard for us to conclude as to whether these were required or not, although in our sample c-sections are highly linked to age (which is a predictor of a higher risk pregnancy).

Table 6
Management of PHC by doctors.

	Means		
	Treatment (1)	Control (2)	Difference (3)
PHC received monthly attendance report	0.53 [0.50] 515		
Staff leave accounts updated based on report	0.47 [0.50] 502		
Faced problem with PHC staff in last three months	0.19 [0.39] 108	0.13 [0.34] 151	0.032 (0.048) 259
Issued show cause notice in the last three months	0.07 [0.26] 108	0.09 [0.28] 151	−0.021 (0.033) 259
Dismissals	0.05 [0.28] 141	0.09 [0.43] 182	−0.067 (0.045) 323

Note: This table provides information on how doctors manage the PHC staff and enforce disciplinary rules.

sector), thus defeating the government's intention of reducing health care costs for the poor, as the women both paid a higher overall price for the deliveries and faced a reduction in the state-sponsored entitlements.

4. Challenges to reform

It is important to note that the idea for the original reform did not stem from the research team: the government identified the absence problem, conceived the program, developed the software, and piloted the equipment in a handful of PHCs in Bengaluru prior to the involvement of the researchers in the project. They also independently raised the money for the project. When we joined, we provided numerous insights from previous research on how to improve both the software and program design that were incorporated in the intervention that was rolled out, but ultimately, it was the government's idea to devise a way to more closely monitor the PHC staff.

Despite this "institutional and senior leadership ownership," the project was plagued with both delays and inadequacies in implementation. The government did not procure the machines until seven months after the planned program start date, and they rolled out the program to the first district eleven months after that date. Even at the first training sessions, when there should perhaps be the most enthusiasm and dedication over a new initiative, one program officer deputed from the state headquarters announced to the local PHC staff her reluctance to deduct their leave balances and salaries if the staff did not comply with the system and attendance rules. Despite the fact that the PHCs were inputting data on most days, the government did not systematically follow up: as Table 6 shows, in only about half the cases that we conducted a random check had the doctor even received the monthly attendance report from the state government the previous month.

The idea of using the more accurate attendance data to better enforce the existing government payment rules, in the end, just never happened. As we described above, the process of deducting leave days is actually quite complex and requires cooperation among different government stakeholders; thus in practice these deductions rarely ever occurred. "Show cause notices," the official document needed to start the process of deducting leaves, were rarely issued. For example, only 9 percent of doctors in the control group had issued at least one notice—for any reason—to one of his or her staff members in the last three months, and there was no difference in the issuing of notices between the treatment and control group (Table 6). Interestingly, despite the better data on delinquencies, there were actually fewer cases of outright dismissal in the treatment group than in the control group, though not significantly so (Table 6).

The implementation challenges stemmed from both the top—i.e. the state government—and the local bureaucrats and politicians who are responsible for further monitoring the PHC staff. At the top, the state government officials, who conceived the project, did not always follow through. Part of this came from a split focus among a variety of initiatives and responsibilities; for example, at one point, the project was slowed down for a month as the government team working on this project was drawn into leading an investigation of a fire at an old age home. At another point, the government forgot to pay its phone bill, leading the system to temporarily shut down.

However, the reluctance was more systematic and reflected the government's overall challenges and tradeoffs in running a public health care system. As discussed earlier, vacancies are prevalent; it is tough recruiting doctors to work in rural health centers, especially given the demand for health care professionals in the private sector in urban areas.[41] Doctors are not always satisfied with the monetary benefits: 25 percent of current doctors claimed to be dissatisfied with this salary, and only 15 percent claimed to be very satisfied with it. As a result, despite believing that the staff needed to be present, the government officials stated that they were reluctant to place too many expectations on the staff, particularly the doctors, in order to provide more flexible work schedules for them. For example, they raised the number of exemptions for doctors from 3 to 5 during the program design. Similarly many local supervisors talked of the unreasonableness of the official working days that require health staff to be present at the PHCs all seven days of the week (six full days and half day on Sundays). They blamed politicians for increasing these work hours to "please" the voters, without any regard for the work-life balance of health staff. So it was no surprise that the program was not eventually scaled up. When we presented the final results to the government, it became clear that just installing the technology and hoping it would lead to an increase in attendance was not sufficient. For the technology to serve its intended purpose, the government would have to enforce the existing penalties on absentee doctors revealed by the data. Senior officials decided not to scale up the program and wind the pilot down, citing an inability and unwillingness at all political and bureaucratic levels to enforce the penalties.

It is not unclear that this fear of antagonizing the doctors, given these other pressures, is entirely unreasonable. As shown in Table 7, in the endline survey, the doctors and nurses in treatment PHCs expressed more dissatisfaction with their job.[42] As shown in Column 1, staff in the treatment group are unhappier with the overall work environment, but this is not significant at conventional levels (p-value of 0.21 in Panel A). Those in the treatment group are less satisfied with the location of the PHC (Column 2) and with the weekly holidays given (Column 8). Interestingly, although doctors claim to be happier with the attendance of the staff who report to them (Column 11), they are less happy with the power or authority given to them to manage the PHC (Column 10). A joint test rejects

[41] The private sector accounts for roughly 80 percent of health care spending in India, much of it in urban areas (PricewaterhouseCoopers Report on Health Care in India, 2007).

[42] In Columns 1–9, we pool together the nurse and doctor samples; Columns 10–12 explore outcomes that are specific to doctors. All regressions include subdistrict fixed effects and are clustered by PHC.

Table 7
Staff satisfaction measures.

	Doctors and Nurses									*Doctors*		
	Overall work environment	Location of PHC	Condition of PHC building and equipment	Salary and benefits	Job stability	Opportunities for professional growth	Work load	Weekly holidays given	Appreciation by community	Power or authority for managing PHC	Attendance of PHC staff who report to you	Performance of PHC staff who report to you
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. All Staff												
Treat	−0.0374	−0.0610**	−0.00778	−0.0378	0.0471	0.0134	0.0374	−0.109**	−0.0309	−0.103**	0.0586	−0.0174
	(0.0298)	(0.0309)	(0.0420)	(0.0488)	(0.0332)	(0.0482)	(0.0455)	(0.0475)	(0.0205)	(0.0450)	(0.0361)	(0.0381)
Observations	439	437	439	438	433	424	437	436	434	259	259	259
Control group mean	0.916	0.928	0.765	0.610	0.850	0.632	0.616	0.690	0.972	0.914	0.907	0.921
Panel B. Only Staff who Joined Prior to Implementation												
Treat	−0.0402	−0.0741**	0.00335	0.0308	0.0219	0.0291	0.0113	−0.0992*	−0.0599**	−0.0538	0.0683	−0.0118
	(0.0352)	(0.0330)	(0.0480)	(0.0558)	(0.0379)	(0.0553)	(0.0520)	(0.0518)	(0.0245)	(0.0499)	(0.0416)	(0.0421)
Observations	333	332	333	332	331	322	331	330	330	190	190	190
Control group mean	0.921	0.941	0.762	0.593	0.877	0.634	0.601	0.704	0.984	0.909	0.900	0.927

Note: This table provides the reduced form effect of belonging to a treatment PHC on employee satisfaction. All regressions are estimated by OLS, include sub-district fixed effects, and are clustered by primary health center. Each outcome is a dummy variable where 1 indicates satisfied or very satisfied and 0 otherwise. All staff members that we interviewed are listed in Panel A, while we restrict the analysis to only those who joined prior to the implementation of the program in Panel B. Note: For all staff jointly (Panel A), the joint chi-sq test across the variables has a value of 31.70 with prob > chi-sq = 0.0015. For only existing staff (Panel B), the joint chi-sq test has a value of 25.11 with prob > chi-sq = 0.0143. ***$p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table 8
Movement into and out of the PHCs.

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)
Panel A: Indicator Variable for Left				
Treat	0.0103	−0.0183	−0.0352	−0.0126
	(0.0176)	(0.0221)	(0.0375)	(0.0258)
Control group mean	0.262	0.269	0.340	0.239
Panel B: Indicator Variable for Joined After Implementation Began				
Treat	−0.0213	−0.0442**	−0.0316	−0.0523**
	(0.0154)	(0.0202)	(0.0366)	(0.0215)
Control group mean	0.177	0.180	0.211	0.167
Observations	3037	1772	514	1258
Panel C: Number of Staff at each Followup				
Treat	−0.0941	−0.122	−0.0115	−0.116*
	(0.113)	(0.0767)	(0.0429)	(0.0623)
Observations	1361	1361	1361	1361
Mean of control group	7.656	4.482	1.280	3.202

Note: In Panel A and B, an observation is an individual and the outcome is an indicator variable, respectively, for whether the individual either left or joined the survey at any point in time. In Panel C, the observation is a PHC at the given followup, and the outcome is the number of staff members employed at that point in time. ***p < 0.01.

** p < 0.05.

* p < 0.1.

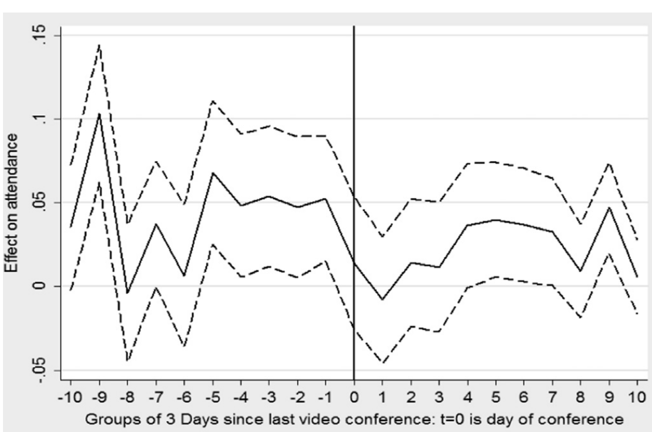

Fig. 5. Event study for video conferences on attendance. Note: The figure above represents a regression of daily attendance (as measured by the IMIDSS system) on 20 dummy variables (in sets of three days) of time before and after the three video conferences (relative to days that were not within two months of the video conferences). We control for day of the week, month of the year, whether a random check was conducted on that day at the PHC, and sub-district fixed effects. The dotted lines represent 95 percent confidence interval around the coefficients; the standard errors are clustered by PHC.

the null that there is no effect across all the satisfaction measures (p-value of 0.001 in Panel A and 0.0143 in Panel B).

As part of the experiment, we worked with the government to freeze transfers across the PHCs. However, individuals may nonetheless choose to leave and others may join. Moreover, new employees have some choice over their placements: when they are hired, there is a counseling session in which they can express their location preferences, with those who score higher on placement exams having a greater probability of receiving their preferences. Thus, in Table 8, we more formally test whether the treatment PHCs exhibited greater difficulty in retaining and hiring new staff. In Panel A, we present coefficients from a regression of an indicator variable for whether the staff member left on treatment status and sub-district fixed effects; in Panel B, the outcome is whether the staff member joined. In Panel C, we explore the total number of individuals employed in that category.

On net, the treatment resulted in fewer lower-level medical staff (for whom we observed an effect of the treatment), but had no effect on doctors (for whom the additional monitoring had no observable effect). New doctors were less likely to join the PHC, but the effect was not significant and the rate was similar to the percentage that left. In contrast, new staff for lower level positions —nurses, lab technicians and pharmacists—were significantly less likely to join the treatment PHCs than the control and at a rate that exceeded exit out of the treatment group. Thus, as a result of the project, there were about 3 percent fewer lower-level medical staff in the treatment group (Column 4, Panel C).[43]

The low level of staff expectations and reluctance and/or inability to fully enforce the existing rules also is present among the local-level bureaucrats and politicians in charge of monitoring the PHCs. The 15 sub-district health officers that we interviewed reported low expectations for staff attendance, despite the formal rules on the books. These low expectations translated into approving almost all of the “exemptions” that the treatment doctors asked for as part of the system, which thus helped the doctors bypass the attendance rules that the machines aimed to enforce. In fact, it appears that attendance is not particularly salient within the set of criteria that they use to evaluate the PHCs: when we asked them to rank the PHCs in their sub-district from best performing to least performing, we find no relationship between their rankings and the attendance of the staff (Appendix A Table 16).

Even when the government tried to motivate the sub-district officers to better implement the system, it appeared to be ineffective. The Director of the National Rural Health Mission of Karnataka set up simultaneous video conference calls with all sub-district officials on three separate occasions to chastise them for the poor attendance of the PHC staff that they managed and to remind them to ensure that the staff were using the machines and formally reporting leave days. During these meetings all the district and sub-district level officials profusely apologized for their lapses and enthusiastically promised to devote their full and immediate attention on following up on the absenteeism data that was being shared with them. As we know the dates of the video conferences, and have detailed daily attendance from the machines, we can conduct an event analysis to test the impact of these video conferences. Fig. 5 shows no systematic increase in staff presence in the days following the video conferences, suggesting that the local bureaucrats did not follow up successfully with the PHCs to increase attendance even when reminded to by the state government. In short, these lower level bureaucrats may have had little incentive to enforce the rules: if they enforce them, the health officers would have to handle complaints by PHC staff and get no personal return in terms of their careers.

[43] We attempted to quantify the characteristics of those who left and joined, although the results are inconclusive. Doctors who left the treatment PHCs had relatively lower attendance than those who joined the control PHCs in the baseline, but the NLP who left were those who attended more in the baseline (Appendix Table 14). There is some qualitative evidence that the new staff nurses who joined the treatment PHCs were relatively more likely to live closer to the PHC than those who joined the control—i.e. they were willing to travel further not to be in the treatment group—but this is not significant at conventional levels (Appendix Table 15).

5. Conclusion

Developing countries often have extensive, and quite stringent, rules governing the responsibilities of government bureaucrats, as well as the supposed penalties in place if they violate those rules. And, yet, in spite of—or perhaps, in some ways, because of—these extensive rules and systems, service provision and quality remains low. One view is that bureaucratic reform, either to improve these rules or even just to better enforce the ones on the books, will be fruitless: countries are beholden to their past institutional design (Acemoglu 2006, Acemoglu et al., 2001) and these designs in developing countries are often characterized by a myriad of confusing rules that few fully know or understand, with complicated bureaucratic structures in place that leave no one fully responsible for enforcing them (Devarajan et al., 2003). Thus, inefficiency and corruption remain the norm.

second view is that reform is possible, especially with technological solutions that can bypass the poor incentives, overlapping institutional structures and individual discretion failures that make it easier for bureaucrats to ignore the existing rules and extract rents—i.e., technology can solve the “principal-agent-citizen problem.”

In this paper, we provide support for the second view: there are potential returns to implementing a technology to better ensure that government workers adhere to formal rules. In particular, we show that the introduction of a monitoring technology to reduce health worker absenteeism led to a small increase in presence and improvement in some birth outcomes. However, we also show that while monitoring may work for some—e.g. nurses—it does not work for others—e.g. doctors—that may have better outside options. Moreover, while there were gains in staff presence, the gains were restricted due to a combination of inflexible and archaic civil service rules and a host of implementation challenges, inherent in most government systems, which are proposed by proponents of the first view.

While promising in that the study showed that greater access to health care can improve health outcomes in developing countries, it also speaks to the fact that we may need to re-evaluate how we think about introducing monitoring technologies in practice. For example, perhaps increasing nurses—whom we can monitor better—relative to doctors would be most beneficial? Or given the low public sector salary, combining increased monitoring for doctors with more realistic expectations of work behaviors (e.g. shorter work week, more days off, fewer days in rural areas) may ensure that they actually complete their assigned work? Clearly, when designing and implementing better monitoring mechanisms or introducing new technology to solve intransigent problems, the devil is in the details, and therefore this continues to be a promising topic for future research.

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Appendix A

See Fig. A1.
See Tables A1-A16.

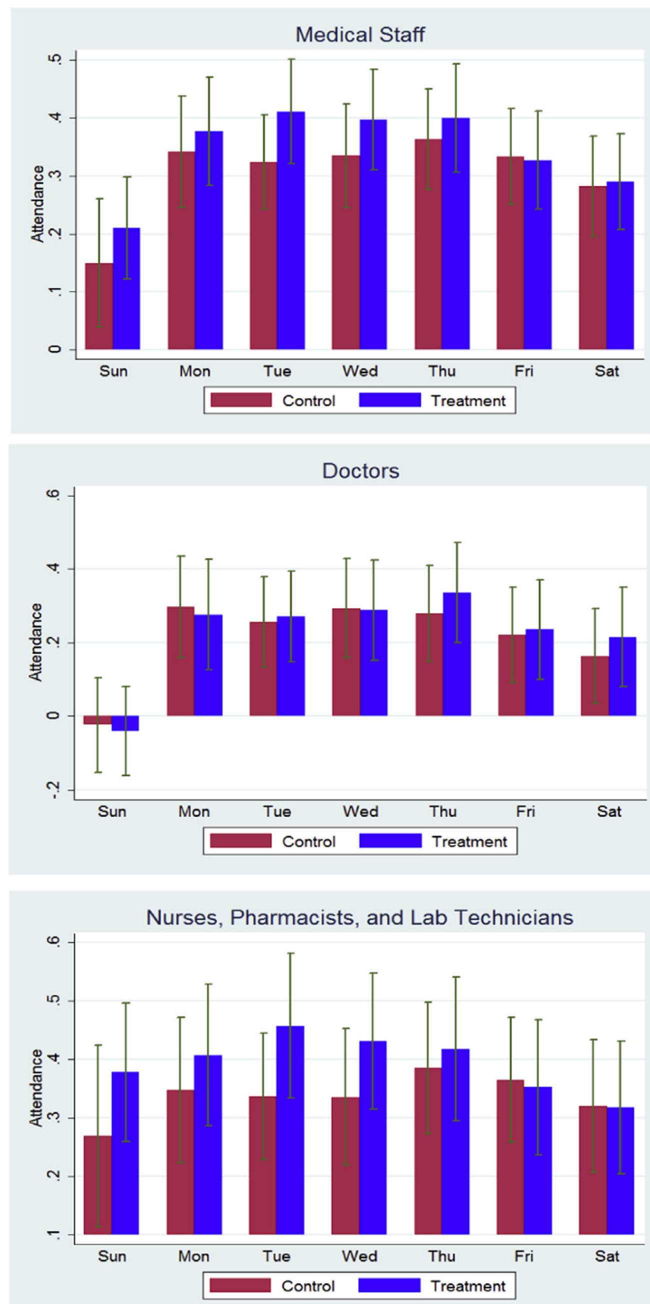

Fig. A1. Attendance, by day of the week.

Table A1
Attrition check on endline survey.

	Doctors (1)	Nurses (2)
Treat	0.0512	0.0531
	(0.0450)	(0.0515)
Observations	323	323
Mean of control group	0.165	0.440

Note: The outcome variable is an indicator variable for a PHC not being surveyed, either due to having a vacancy in the position or due to the staff member being repeatedly unavailable during the survey. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A2
Effect of treatment on infant mortality.

	Indicator for stillbirth or miscarriage (1)
Treat	0.00166
	(0.00314)
Observations	2598
Control group mean	0.00413

Note: This table looks at the effect of belonging to the catchment area of a PHC group on still births and miscarriages. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A4
Test for Hawthorne effects.

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
Monitoring status	0.0110	0.00466	0.0134	-0.00358	0.0344
	(0.00797)	(0.0102)	(0.0164)	(0.0119)	(0.0215)
Observations	8084	4659	1363	3296	1440

Note: This table provides the reduced form effect of being monitored more heavily in the random checks, by type of staff member. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. If the baseline value is missing, we assign the average baseline attendance and include a dummy variable for when the baseline value was imputed. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A3
Randomization check.

	Mean		
	Treatment (1)	Control (2)	Difference (3)
A: Facility Survey			
Number of Sub-Centers	4.81	4.46	0.06
	[2.52]	[2.37]	(0.23)
24/7 PHC	0.4	0.38	-0.05
	[0.49]	[0.49]	(0.05)
Number of daily patients	67.42	65.87	-0.3
	[41.64]	[39.18]	(4.62)
Number of examination beds	0.79	0.79	-0.02
	[0.9]	[0.88]	(0.1)
Has working toilet	0.75	0.79	-0.04
	[0.43]	[0.41]	(0.04)
Has drinking water	0.77	0.75	0.03
	[0.42]	[0.44]	(0.05)
Has broken windows	0.3	0.25	0.01
	[0.46]	[0.44]	(0.05)
Has clean walls	0.53	0.51	0.01
	[0.50]	[0.50]	(0.06)
Has clean floors	0.58	0.49	0.08
	[0.49]	[0.50]	(0.05)
Has pharmacy	0.89	0.87	0.00
	[0.32]	[0.34]	(0.04)
Number of medicines in stock	8.43	8.30	-0.02
	[2.76]	[3.12]	(0.31)
Number of vaccines in stock	4.77	4.81	0.02
	[2.33]	[2.26]	(0.25)
B. Attendance Measures			
All staff	0.45	0.43	0.04*
	[0.21]	[0.17]	(0.02)
Medical staff	0.44	0.43	0.02
	[0.26]	[0.24]	(0.03)
Doctor	0.34	0.37	0.00
	[0.36]	[0.35]	(0.04)
Nurse, lab technician, pharmacist	0.5	0.48	0.03
	[0.30]	[0.31]	(0.03)

Note: This table provides a check on the randomization. For the facility data (Panel A), the joint chi-sq test across the variables with fixed effects has a value of 7.71 with prob > chi-sq = 0.8070. For the attendance data (Panel B), the joint chi-sq test with fixed effects has a value of 5.24 with prob > chi-sq = 0.2635.

Table A5
Monitoring by sub-district and community.

	Sub-district health officer		Community			
	Visited the PHC in last month (dummy)	Number of visits the sub-district officer conducted	MO attended GP meeting in past 3 months (dummy)	Number of meetings MO attended	GP inspected PHC in past 3 months (dummy)	Number of inspections GP conducted
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−0.0288	−0.109	−0.0376	0.114	0.0765	−0.112
	(0.0504)	(0.109)	(0.0685)	(0.242)	(0.0510)	(1.050)
Observations	143	143	185	186	186	186
Control group mean	0.414	0.671	0.685	1.387	0.817	4.237

Note: This table explores whether the sub-district health officers and local government bodies differentially monitored the PHCs by treatment status. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A6
Reduced form effect on presence (random checks), robustness to controls.

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
A. No Baseline Measure					
Treat	0.0349**	0.0529***	0.0142	0.0714***	0.0113
	(0.0137)	(0.0166)	(0.0264)	(0.0197)	(0.0386)
Observations	8084	4659	1363	3296	1440
Control group mean	0.396	0.373	0.309	0.401	0.573
B. No Baseline Measure Nor Sub-District Fixed Effects					
Treat	0.0204	0.0380**	−0.00594	0.0521**	0.0457
	(0.0163)	(0.0192)	(0.0280)	(0.0227)	(0.0395)
Observations	8084	4659	1363	3296	1440
Control group mean	0.396	0.373	0.309	0.401	0.573
C. Gender, Years at PHC, Baseline Attendance and Sub-district Fixed Effects					
Treat	0.0324**	0.0539***	0.00954	0.0739***	
	(0.0137)	(0.0164)	(0.0265)	(0.0194)	
Observations	8084	4659	1363	3296	
Control group mean	0.396	0.373	0.309	0.401	

Note: This table replicates Table 3, but varies the control variables that are included. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS and are clustered by PHC. If a control variable has a missing value, we assign the average and include a dummy variable to indicate when it was imputed. *p < 0.1.

*** p < 0.01.
** p < 0.05.

Table A7
Reduced form effect on presence (random checks), robustness to sample.

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
Panel A: Including New Staff Members					
Treat	0.0288**	0.0444***	0.00434	0.0642***	0.0102
	(0.0129)	(0.0161)	(0.0269)	(0.0179)	(0.0384)
Observations	9057	5235	1553	3682	1441
Control group mean	0.394	0.373	0.306	0.403	0.573
Panel B: Balanced Panel Only					
Treat	0.0357**	0.0575***	0.0353	0.0714***	0.0143
	(0.0145)	(0.0171)	(0.0287)	(0.0203)	(0.0380)
Observations	7117	4162	1152	3010	1435
Control group mean	0.415	0.387	0.313	0.416	0.573

Note: This table replicates Table 3, but varies the included sample. In Panel A, we include everyone, including staff members that joined the PHC. In Panel B, we only include staff members who were present in all follow-up rounds. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS, include the baseline attendance measure, and are clustered by PHC. *p < 0.1.

*** p < 0.01.
** p < 0.05.

Table A8
Presence results, by staff type.

	(1)
Treat × "Doctor Dummy"	−0.0274
	(0.0239)
Treat × "Nurse Dummy"	0.0798***
	(0.0226)
Treat × "Lab Tech or Pharmacist Dummy"	0.0989***
	(0.0275)
Test Doctors = Nurses	
F(1,320)	13.66
Prob > F	0.0003
Test Doctor = L/P	
F(1,320)	14.78
Prob > F	0.0001
Test Nurse = L/P	
F(1,320)	0.31
Prob > F	0.5795
Observations	4,659
Control Group Mean	0.373

Note: This table estimates the treatment effect (from Table 3) separately by doctor, nurse, and lab technician/pharmacist. The regression is estimated by OLS, includes the baseline attendance measure, and is clustered by PHC. **p < 0.05, *p < 0.1.
*** p < 0.01.

Table A9
Reduced form effect on staff presence, by time of day (random checks).

	Medical staff (1)	Doctors (2)	Nurse, lab technician, pharmacist (3)
Treat*9–10a.m.	0.162***	0.134***	0.177***
	(0.0281)	(0.0466)	(0.0324)
Treat*11a.m.–12p.m.	-0.0191	-0.0723	0.00730
	(0.0327)	(0.0543)	(0.0363)
Treat*1–2p.m.	0.0206	-0.0436	0.0480
	(0.0325)	(0.0577)	(0.0381)
Treat*3–4p.m.	0.0290	0.0237	0.0347
	(0.0329)	(0.0589)	(0.0398)
Observations	4,659	1,363	3,296
Mean of control group	0.373	0.309	0.401

Note: This table explores the effect of belonging to the treatment group on staff presence, by time of day. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. **p < 0.05,
*** p < 0.01,
* p < 0.1

Table A10
Reduced form effect on presence by district (random checks).

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
Panel A. Mysore					
Treat	0.0208	0.0390	−0.0390	0.0810**	−0.0162
	(0.0247)	(0.0327)	(0.0416)	(0.0404)	(0.0678)
Observations	3329	1825	652	1173	657
Control Group Mean	0.412	0.388	0.344	0.412	0.526
Panel B. Dakskin Kannada					
Treat	0.0383	0.0858**	0.0866	0.0838*	−0.0131
	(0.0297)	(0.0379)	(0.0602)	(0.0445)	(0.0790)
Observations	1268	753	227	526	244
Control group mean	0.442	0.426	0.305	0.478	0.589
Panel C. Chitradurga					
Treat	0.0767**	0.0676*	0.0288	0.0938**	−0.00360
	(0.0294)	(0.0348)	(0.0545)	(0.0448)	(0.0838)
Observations	1472	883	246	637	281
Control group mean	0.372	0.339	0.265	0.365	0.598
Panel D. Dharwad					
Treat	0.0346	0.0702	−0.0186	0.0969**	0.112
	(0.0447)	(0.0435)	(0.119)	(0.0428)	(0.109)
Observations	772	444	89	355	106
Control group mean	0.342	0.353	0.308	0.364	0.647
Panel E. Bidar					
Treat	0.0107	0.0282	0.0851	0.00562	0.0554
	(0.0329)	(0.0322)	(0.0778)	(0.0351)	(0.0735)
Observations	1243	754	149	605	152
Control group mean	0.330	0.297	0.152	0.338	0.766

Note: This table replicates Table 3, by district. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. If the baseline value is missing, we assign the average baseline attendance and include a dummy variable for when the baseline value was imputed. *** p < 0.01.
** p < 0.05.
* p < 0.1.

Table A11
Reduced form effect on presence (random checks), heterogeneity by PHC type.

	All staff (1)	Medical staff (2)	Doctors (3)	Nurse, lab technician, pharmacist (4)	Indicator for doctor or nurse presence (5)
Treat	0.0600***	0.0809***	0.00137	0.126***	0.0494
	(0.0206)	(0.0263)	(0.0348)	(0.0335)	(0.0453)
24 × 7 PHC	–0.00409	0.00673	−0.00339	−0.0145	0.426***
	(0.0186)	(0.0241)	(0.0374)	(0.0295)	(0.0412)
Treat × 24 × 7 PHC	–0.0514*	−0.0553*	0.0356	−0.0987**	−0.0828
	(0.0270)	(0.0329)	(0.0533)	(0.0398)	(0.0616)
Observations	8084	4659	1363	3296	1440
Mean of control group	0.396	0.373	0.309	0.401	0.573

Note: This table replicates explore the effect of belonging to the treatment group, by whether the PHC is open 24 h a day. In Columns 1 to 4, an observation is an individual staff member and the outcome is a dummy variable that indicates whether that staff member was present; in Column 5, an observation is a PHC and the outcome is a dummy variable for whether at least one nurse or doctor is present. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. If the baseline value is missing, we assign the average baseline attendance and include a dummy variable for when the baseline value was imputed.
*** p < 0.01.
** p < 0.05.
* p < 0.1.

Table A12
Number of patients.

	Patients waiting at PHC (1)	Patients in beds (2)	Women in beds for childbirth (3)
Treat	0.317	−0.0855	−0.0106
	(0.390)	(0.0786)	(0.0247)
Observations	1433	1433	1433
Control group mean	3.553	0.393	0.101

Note: This table explores the effect of belonging to the treatment group on the number of patients present. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A13
Reduced form effect on satisfaction and costs (pregnancy survey), heterogeneity by delivery.

	Log (Cost) (1)	Knowledge (2)	Received (3)
Treat	0.582***	−0.183***	−0.0763
	(0.198)	(0.0672)	(0.0979)
Delivery at PHC	−2.150***	0.165***	0.545***
	(0.364)	(0.0582)	(0.110)
Treat*Delivery at PHC	0.135	0.0435	−0.0419
	(0.514)	(0.112)	(0.166)
Observations	775	785	785
Control group mean	6.810	2.834	1.861

Note: This table explores the effect of belonging to the treatment group on costs and entitlements, by delivery location. All regressions are estimated by OLS, include a baseline control and sub-district fixed effects, and are clustered by primary health center. **$p < 0.05$.

*** $p < 0.01$.
* $p < 0.1$.

Table A14
Do the staff that left differ in baseline attendance?

	All staff (1)	Medical staff only (2)	Doctors only (3)	N/L/P only (4)
Treat	0.0161	−0.00725	0.0469	−0.0167
	(0.0210)	(0.0254)	(0.0463)	(0.0277)
Left	−0.186***	−0.205***	−0.121***	−0.236***
	(0.0210)	(0.0265)	(0.0461)	(0.0333)
Treat * Left	0.0187	0.0180	−0.169**	0.104**
	(0.0317)	(0.0431)	(0.0676)	(0.0506)
Observations	4653	2706	757	1949
Control group mean	0.386	0.387	0.336	0.408

Note: This table explores the baseline characteristics for those who left the PHC, by treatment status.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$

Table A15
Characteristics of new staff.

	Distance to get to work	Live locally (dummy)
Treat	3.039	−0.0738
	(2.290)	(0.0505)
New	7.771*	−0.145**
	(4.136)	(0.0671)
Treat * New	−4.414	0.0943
	(5.289)	(0.109)
Observations	427	445
Control group mean	14.41	0.555

Note: This table explores the baseline characteristics for those who left the PHC, by treatment status. ***$p < 0.01$.

** $p < 0.05$.
* $p < 0.1$.

Table A16
Correlation between rank quality, presence and treatment.

	Rank (1)	Presence (2)	Presence (3)
Panel A: No Fixed Effects			
Treat	–0.0687	0.0272	0.0746
	(0.0949)	(0.0250)	(0.0563)
Rank		0.0143	0.0730
		(0.0521)	(0.0887)
Treat * rank			−0.0927
			(0.120)
Panel B: Include Sub-District Fixed Effects			
Treat	–0.0720	0.0398	0.0972
	(0.106)	(0.0223)	(0.0637)
Rank		0.0163	0.0864
		(0.0543)	(0.0870)
Treat * rank			−0.110
			(0.111)
Observations	82	82	82
Control group mean	0.536	0.351	0.351

Note: This table explores relationship between the sub-district health officials rankings of PHCs in their sub-district, attendance, and rankings. ***$p < 0.01$, **$p < 0.05$.

* $p < 0.1$.

Appendix B. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jdeveco.2016.08.008.

References

Acemoglu, Daron, 2006. A simple model of inefficient institutions. Scand. J. Econ. 108, 515–546.
Acemoglu, Daron, Johnson, Simon, Robinson, James A., 2001. The colonial origins of comparative development: an empirical investigation. Am. Econ. Rev 91 (5), 1369–1401.
Alatas, Vivi, Banerjee, Abhijit, Olken, Benjamin, Purnamasari, Ririn, Wai-Poi, Matthew, 2013. Does Elite Capture Matter? Local Elites and Targeted Welfare Programs in Indonesia. Working Paper no. 18798. National Bureau of Economic Research.
Andrabi, Tahir, Das, Jishnu, Ijaz Khwaja, Asim, 2016. Report Cards: The Impact of Providing School and Child Test Scores on Educational Markets. Working Paper.
Ashraf, Nava, Bandiera, Oriana, Lee, Scott S., 2015. Do-Gooders and Go-getters: Career Incentives, Selection, and Performance in Public Service Delivery. Working Paper.
Banerjee, Abhijit, Deaton, Angus, Duflo, Esther, 2004. Wealth, health, and health services in rural Rajasthan. Am. Econ. Rev. 94 (2), 326–330.
Banerjee, Abhijit, Duflo, Esther, Glennerster, Rachel, 2008. Putting a band-aid on a corpse: incentives for nurses in the Indian Public Health Care System. J. Eur. Econ. Assoc. 6 (2–3), 487–500.
Banerjee, Abhijit, Hanna, Rema, Mullainathan, Sendhil, 2013. Corruption. In: Gibbons, Robert, Roberts, John (Eds.), Handbook of Organizational Economics. Princeton University Press, Princeton, pp. 1109–1147.
Banerjee, Abhijit, Chattopadhyay, Raghabendra, Duflo, Esther, Keniston, Daniel, Singh, Nina, 2012. Can Institutions Be Reformed From Within? Evidence From A Randomized Experiment With The Rajasthan Police. Working Paper no. 17912. National Bureau of Economic Research.
Banerjee, Abhijit, Hanna, Rema, Kyle, Jordan, Olken, Benjamin, Sumarto, Sudarno, 2015. Contracting out the Last-Mile of Service Delivery: Subsidized Food Distribution in Indonesia. Working Paper.
Benabou, Roland, Tirole, Jean, 2006. Incentives and prosocial behavior. Am. Econ. Rev. 96 (5), 1652–1678.
Björkman, Martina, Svensson, Jakob, 2009. Power to the people: evidence from a randomized field experiment on community-based monitoring in Uganda. Q. J. Econ. 124 (2), 735–769.
Bold, Tessa, Mwangi, Kimenyi, Mwabu, Germano, Ng'ang'a, Alice, Sandefur, Justin, 2013. Scaling-up What Works: Experimental Evidence on External Validity in Kenyan Education. CSAE Working Paper Series 2013–04. Centre for the Study of African Economies, University of Oxford.
Callen, Michael, Gulzarz, Saad, Hasanain, Ali, Khan, Yasir, 2016. The Political Economy of Public Sector Absence: Experimental Evidence from Pakistan. Working Paper.
Chaudhury, Nazmul, Hammer, Jeffrey, Kremer, Michael, Muralidharan, Karthik, Rogers, F. Halsey, 2006. Missing in action: teacher and health worker absence in developing countries. J. Econ. Perspect. 20 (1), 91–116.

Das, Jishnu, Hammer, Jeffrey, 2005. Which doctor: combining vignettes and item response to measure doctor quality. J. Dev. Econ. 78, 348–383.

Das, Jishnu, Hammer, Jeffrey, 2007. Money for nothing: the dire straits of medical practice in India. J. Dev. Econ. 83 (1), 1–36.

Das, Jishnu, Hammer, Jeffrey, Leonard, Kenneth, 2008. The quality of medical advice in low-income countries. J. Econ. Perspect. 22 (2), 93–114.

Deininger, Klaus, Goyal, Aparajita, 2012. Going digital: credit effects of land registry computerization in India. J. Dev. Econ. 99, 236–243.

Devarajan, Shanta, Easterly, William, Pack, Howard, 2003. The cartel of good intentions: the problem of bureaucracy in foreign aid. J. Policy Reform 5 (4), 1–28.

Duflo, Esther, Hanna, Rema, Ryan, Stephen P., 2012. Incentives work: getting teachers to come to school. Am. Econ. Rev. 102 (4), 1241–1278.

Fujiwara, Thomas, 2015. Voting technology, political responsiveness, and infant health: evidence from Brazil. Econometrica 83 (2), 423–464.

Hanna, Rema, Wang, Shi-Yi, 2014. Dishonesty and Selection into Public Service: Evidence from India. Working Paper no. 19649. National Bureau of Economic Research.

Holstrom, Bengt, Milgrom, Paul, 1991. Multitask principal-agent analyses: incentive contracts, asset ownership, and job design. J. Law Econ. Organ. 7, 24–52.

Muralidharan, Karthik, Niehaus, Paul, Sukhtankar, Sandip, 2014. Building State Capacity: Biometric Identification and the Delivery of Public Programs in India. Working Paper no. 19999, National Bureau of Economic Research.

PricewaterhouseCoopers, 2007. Emerging Market Report: Health in India, 2007.

Siega-Riz, Anna Maria, Hartzema, Abraham G., Turnbull, Craig, Thorp, John, McDonald, Thad, Cogswell, Mary E., 2006. The effects of prophylactic iron given in prenatal supplements on iron status and birth outcomes: a randomized controlled trial. Am. J. Obstet. Gynecol. 194 (2), 512–519.

Yasmin, Sohely, Osrin, David, Paul, Elizabeth, Costello, Anthony, 2001. Neonatal mortality of low-birth-weight infants in Bangladesh. Bull. World Health Organ. 79 (7), 608–614.

Zeng, Lingxia, Cheng, Yue, Dang, Shaonong, Yan, Hong, Dibley, Michael J., Chang, Suying, Kong, Lingzhi, 2008. Impact of micronutrient supplementation during pregnancy on birth weight, duration of gestation, and perinatal mortality in rural western China: double blind cluster randomised controlled trial. Br. Med. J., 337.